

Aalto University
School of Science
Master's Programme in International Design Business Management

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Factors influencing consumers' adoption and use of wearable technologies

Master's Thesis

Espoo, March 12, 2019

Supervisor: Professor Matti Vartiainen

AALTO UNIVERSITY
 School of Science
 Master's Programme in International Design Business Management

ABSTRACT OF THE
 MASTER'S THESIS

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Title of the thesis: Factors influencing consumers' adoption and use of wearable technologies	
Number of pages: 53 + 2	Date: March 12, 2019
Major: International Design Business Management	
Supervisor: Matti Vartiainen	
Thesis advisor: Matti Vartiainen	
<p>Inactivity and increase in chronic health conditions caused by sedentary behavior have become a growing concern in many countries. In the past years, many health and wellbeing technologies have been launched to promote healthy behavior and help people to better monitor and track their activity level and performance throughout the day.</p> <p>The main goal of this thesis was to take a closer look at factors influencing consumers' adoption and use of wearable technologies. For this purpose, a theoretical framework was built, highlighting key factors influencing perceived benefits, perceived risks and abandonment of wearable devices.</p> <p>The theoretical framework was tested by conducting an empirical study using netnography. Focus of the empirical study was narrowed down to the consumer market and activity trackers. Data of this study was collected from top rated reviews (N=60) in Amazon for three products: Fitbit Charge 2, Garmin Vivosmart HR+ and Polar A370. Sixty customer reviews were collected and analyzed using Atlas.ti.</p> <p>Results of this study showed that usefulness is the most influential factor on consumers' perceived benefits of a wearable device. Perceived risks are mainly affected by financial and performance risks. Finally, data inaccuracy, build quality, synchronization, poor UI & UX design and system malfunction are the most impactful factors for dissatisfaction and device abandonment.</p>	
Keywords: wearables, technology adoption, wearable retention, activity trackers, netnography	Publishing language: English

Preface

I have always considered technology fascinating. Widespread adoption of wearable devices specially fitness trackers have made me wonder on how effective these devices are in encouraging healthy behavior. When it was time to start my thesis, I took the opportunity to choose my topic around wearable technologies.

After few weeks in the literature review, I realized that I have become very curious about factors behind adoption and abandonment of wearable technologies. So, after an interesting discussion with my thesis supervisor, professor Matti Vartiainen, we agreed to put the focus of the thesis on factors influencing consumers' adoption and use of wearable technologies.

The process of writing this thesis has been both challenging and exciting for me. Specially using netnography as the method of data collection was new for me, and something which I want to use again in the future. I hope this thesis and its findings provide something valuable to you.

Here I would like to thank professor Matti Vartiainen for all his support, guidance and encouragement during the thesis process. I would also like to thank my parents who have supported me throughout all stages of my life.

Espoo, 10.03.2019

Navid Karimian Pour

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1. Introduction

1.1 Background

There has been a growing concern about reduction in daily physical activity and sedentary behavior (Wilde et al., 2018). Healthcare systems are facing with challenges such as, widespread obesity epidemic in the society (Ananthanarayan & Siek, 2012) and, development of chronic health conditions such as type 2 diabetes, cardiovascular disease, and some cancers (Wilde et al., 2018). For example, over 60% of adults in the United States are overweight, which is three times increase since 1991 (Ananthanarayan & Siek, 2012). Some studies show that over half of the Americans neglect following fitness recommendations despite receiving specific instructions from their healthcare providers (Rupp et al., 2016).

Inactivity is not only among adults but also, younger generation. According to Kerner and Goodyear (2017), only 50% of young people do enough physical activity to achieve positive health benefits. Several reasons cause insufficient physical activity and obesity among people from which, lack of motivation to engage in physical activity, poor dietary choices and limited knowledge on how to include physical activity in the daily life stand out (Ananthanarayan & Siek, 2012; Rupp et al., 2016). Low levels of physical activity and the health conditions resulted from that could have a significant impact on the economy due to increase in healthcare costs and decrease in productivity (Wilde et al., 2018).

Technology has been seen to be negatively related to physical activity. However, in the past decade, there has been a trend in developing health and life style technologies such as wearable fitness devices and mobile health applications which promote increase in physical activity and healthy life style (Kerner & Goodyear, 2017). These technologies collect and monitor users' data on physical activities (Kerner & Goodyear, 2017) and can act as a medium for delivering information and recommendations to the user (Asimakopoulos et al., 2017). Since users regularly use mobile and wearable devices, it could be a good tool for motivating and encouraging them in improving healthy behavior and physical activity (Asimakopoulos et al., 2017).

There has been a growing interest among scholars to conduct research on wearables, healthy behavior and interrelation between them. Some of these studies are focusing mainly on factors driving adoption intention to wearables. For example, Chuah et al. (2016) conducted an empirical study utilizing the technology acceptance model (TAM) to understand factors driving adoption intention to smartwatches. Lunney et al. (2016)

combined variables from TAM and the theory of planned behavior (TBP) to understand factors affecting the adoption of wearable technologies.

Beside technology adoption, there has been an increasing interest in evaluating performance and effectiveness of wearables. Some of these studies have a general focus on impacts of wearables on overall wellbeing, physical activity and usability (Fritz et al., 2014; Laet, 2017; Gal et al., 2018; Lim et al., 2018). Others, narrowed down their focus on a specific area or a target group such as sleep (De Arriba-Pérez et al., 2018; Peake et al., 2018; Hossain et al., 2018), well-being at workplace (Giddens et al., 2017; Cotie et al., 2018), measurement accuracy (Lang, 2017), adolescent's motivation (Kerner & Goodyear, 2017), sedentary adults (Sullivan & Lachman, 2017), chronic diseases (Wang et al., 2015; Alturki & Gay, 2016; Moy, 2016) and so on.

1.2 Research Objective

The main objective of this thesis is to provide a more holistic understanding about factors influencing consumers adoption and use of wearable technologies. In other words, the goal of this thesis is to investigate why an individual acquires a wearable device, how effective wearables are in influencing healthy behavior, why a high percentage of users stop using their device after a certain period of time and how design and usability of wearable devices can be improved.

To address the thesis objective, literature related to human behavior and motivation, theories and models of technology adoption and previous studies on adoption and effectiveness of wearable technologies will be reviewed. Based on the literature review, a theoretical framework will be presented. Theoretical framework of the thesis will then be validated by conducting an empirical study.

1.3 Structure of the Thesis

This thesis is divided into five chapters. The content and objectives of the chapters are as follows. Chapter 1 introduces background and the main objective of the thesis. Chapter 2 discusses the theoretical background of the thesis by reviewing literature related to human behavior, motivation theories, technology adoption models, factors behind adoption, use and abandonment of wearable technologies. Chapter 3 shows research design and methodology by first introducing research questions. Then data collection, analysis methods and study procedure are explained. Chapter 4 reviews main findings of the thesis and answers to the research questions. Chapter 5 discusses main theoretical and practical implications of the thesis as well as limitations and suggestions for future research.

2. Theoretical Background

2.1 Wearables

2.1.1 Introduction to Wearables

Wearables are smart electronic devices embedded with computing systems (Williamson et al., 2015). Wearables are intended to be worn by people constantly (Rupp et al., 2016) as an accessory or embedded in clothing (Yang et al., 2016). Wearables can resemble a watch, contact lenses, eyeglasses, clothing, shoes or jewelry (Salah et al., 2014). Figure 1 is a simple demonstration of wearables in different forms.

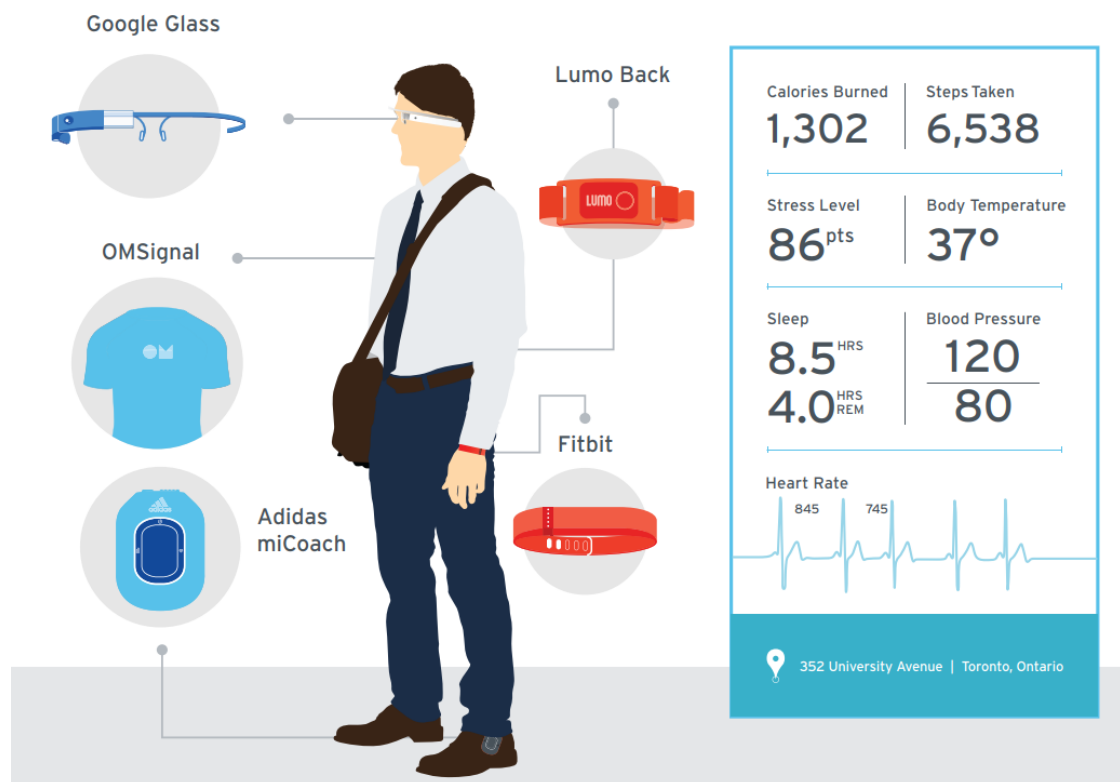


Figure 1. Wearables in different forms (Adapted from Salah et al., 2014, p. 5).

Wearables primary function is sensing (Williamson et al., 2015). They are equipped with micro-electromechanical sensors enabling them to capture and measure human biological data such as body movements, heart rate, breath quality, sleep and brain activity (Hänsel et al., 2015; Asimakopoulos et al., 2017). This data is then processed by the wearable device itself or transferred to a remote device such as a mobile phone for processing (Williamson et al., 2015). Majority of the wearable devices provide the user with feedback and demonstrate information including step count, calories burned, stairs

climbed, distance travelled and sleep quality. Some devices provide additional functionalities such as social sharing and social interaction with other users in the form of competition, cooperation or comparison (Asimakopoulos et al., 2017).

2.1.2 Wearable Categories

Wearables can be categorized in different ways. Salah et al. (2014) categorized wearables based on market segments to consumer and non-consumer segments. They further broke down these two categories to the following target sectors:

- Consumer market segment
 - General consumers
 - Fitness and sports
 - Fashion and apparel
 - Home automation and remote identification
 - Gaming and recreation
- Non-consumer segment
 - Defense and security
 - Enterprise and industrial
 - Healthcare

From functionality perspective, Lunney et al. (2016) divided wearables into three categories: notifiers, glasses and trackers. Notifiers give information about surrounding world such as smart watches. Glasses provide an augmented virtual reality capability for the user. Trackers utilize sensors to record data, for instance fitness trackers.

Wearables can be equipped with one or several sensors measuring variety of things. Hänsel et al. (2015) stated that six sensors are commonly used in wearables: accelerometers, stretch sensors, piezoelectric sensors, heart rate sensors, UV sensors and GPS. Accelerometers are used to measure movements and activity. Stretch sensors or electromyographic embedded in clothing measure muscle activity. Piezoelectric or pressure sensors measure force applied to them. Heart rate sensors or electrocardiogram (ECG) measure the activity of heart for more accurate calculation of the energy consumption. UV sensors evaluate amount of UV light to give warning if there is too much exposure to sun light. Finally, GPS is used for localization.

This thesis focuses on the consumer market segment and only on the trackers category. Therefore, from now on whenever term wearable is mentioned, it is referred to trackers in the consumer market segment.

2.1.3 Why Consumers Use Wearables

Wearable devices have become a trendy consumer item specially in advanced economies (Manyika et al., 2015) and interest in wearables is expected to increase even more in the upcoming years (Lunney et al., 2016). It is estimated that by 2020, there will be 500 million wearable devices owned by consumers (Giddens et al., 2017). There are two key factors behind the rapid adoption of wearable devices. First, technological advancements in areas such as low-power semiconductors and the wide spread adoption of mobile phone devices provided the possibility to produce cheaper wearable devices which are compatible with consumers' mobile devices especially smart phones (Williamson et al., 2015). As a result, consumers can acquire a wearable device for a relatively cheap price, making the technology affordable for many people.

Second, the increase in self-awareness among consumers has intensified the Quantified Self movement (Hänsel et al., 2015), i.e., “use of technology to capture, measure, track and analyze data from a person's daily life” (Salah et al., 2014, p. 4). Consumers have become more interested to track and understand reasons behind changes in their mental and physical status. Since wearable devices are worn continuously, users can record biological data automatically and easily monitor changes and receive feedback through the device (Salah et al., 2014). But what are the reasons behind self-quantification?

It is reported that one of the main reasons of self-quantification is the health improvement (Hänsel et al., 2015). Consumers have become more interested to maintain a healthy lifestyle. So, tracking indicators such as step counts, calories burned, sleep quality and heart beat provided by wearable devices help consumers to get a better understanding of their daily activity and body condition (De Arriba-Pérez et al., 2018). In addition, wearable devices enable consumers to keep track of their achievements and motivate them by providing individual and/or group challenges and competitions (Sergueeva & Shaw, 2017).

Beside health improvement, there are other reasons why consumers adopt and use wearable devices from which the social image stands out. According to Yang et al. (2016), the social image plays an important role in acquiring a wearable device. Since wearable devices are incorporated in items of clothing and accessories, some consumers tend to see them as a fashion item or to show off innovativeness to others. That is why beside functionality, some consumers pay special attention to brand name and visual attractiveness.

2.1.4 Wearables Retention

Wearable technology is getting more advanced and its applications are evolving. However, ensuring long-term user retention is still challenging. The dropout rate of health and fitness wearables is very high, and it is reported to be around 85 percent. (Hänsel et

al., 2015) According to Piwek et al. (2016), 32% of users stop wearing the device after six months and this number reaches to 50% at the end of the first year.

Many factors are seen to be behind the low retention rate of wearable devices. Piwek et al. (2016) considers the poor implementation of user experience, and the reliability of the data provided by wearable devices behind the low retention rate. Hänsel et al. (2015) see the user interface as one of the key factors. They stated that the lack of efficient data collection and utilization could contribute to the retention rate. When data is presented poorly, it may confuse the user more than helping him/her, leading to discouragement and eventually abandonment of the device. Salah et al. (2014) also argue that data collected and presented by some of the wearable devices is inaccurate. Users have complained that some devices for instance undercount or overcount certain activities. In addition, Salah et al. (2014) mentioned that the design of some of the devices is impractical and causes feelings of discomfort when wearing the device. In some cases, sounds and lights generated by wearables may put the user in awkward social situation, or the aesthetics and looks of wearables prevent users to match them with their clothing because the device is not a good fit for different outfits or it is simply ugly.

Schrager et al. (2017) conducted a study to evaluate effectiveness of using wearable devices to track and improve physical activity and the wellness of medical residents during a six-month period. Empirical data of the study was collected via online questionnaires and active data collection. The device used for this study was Fitbit activity tracker. From 59 participants at the beginning of the study, only one third continued using the device for the whole six-month period. Participants who stopped using the wearable device, did so for several reasons. First, some participants were not satisfied with the accuracy of the data collection. They perceived that the device collects the data inaccurately or it is not able to collect physical data for some sports/activities they perform during the day. In addition, losing interest in the device, not wanting to wear the device on the wrist, malfunction, loss, comfort and fashion were reported as other reasons for discontinuation of use. (Schrager et al., 2017)

Clawson et al. (2015) investigated factors behind the abandonment of self-tracking technologies. For this purpose, they analyzed around 1600 advertisements for secondary sales of these devices on Craigslist (American classified advertisements website). The study revealed that there are reasons behind the technology abandonment in addition to the perceived lack of the utility or the feeling of frustration using the device. First, the abandonment due to achieving desired goals or upgrading to a better device. Second, the social switching meaning users switch to another device because of their friends, family or colleagues. Third, there has been a change in physical ability such as illness or changes in physical activities which are associated with the device. Finally, user perceived mismatch between device capabilities and his/her needs which is the most common reason for abandonment. (Clawson et al., 2015)

Harrison et al. (2015) studied barriers to engagement with activity trackers. Data collected for this study came from the survey and contextual interviews with 24 participants. Result of this study showed that one of the main reasons of device abandonment is the inaccuracy in data collection specially in activities which are not step-based. Another reason is the social comparison. Users are interested to share their activities socially, but this could also cause frustrations and abandonments. For example, some users abandon a device and acquired a new one because they were not able to share their activity progress with their friends (among different brands and/or models). Finally, abandoning a device due to aesthetics and form. Many wearable devices have limited options for customizability, making it difficult to match the device for different needs and occasions. (Harrison et al., 2015)

Lazar et al. (2015) studied reasons for abandoning smart devices. In this study the participants were recruited from a technology company and given one thousand dollars to purchase smart devices to advance them towards a goal they were passionate about. After a two-month period, semi-structured interviews were conducted to investigate whether participants experience any benefits from using smart devices. Several reasons were identified for abandoning the smart devices. First, the mismatch between the user's real needs and what the device offers. Second, the poor data presentation and feedback. Third, efforts required to maintain the device such as charging the battery and keeping the device connected (for instance to phone or tablet). Finally, some participants did not find the device comfortable to wear or heavy to carry around. (Lazar et al., 2015)

Epstein et al. (2016) conducted a study to investigate why people abandon self-tracking technologies. Empirical data of this study was collected via survey filled by 193 people and 12 interviews. Authors found six main reasons for the abandonment of self-tracking devices. First, people perceive costs of collecting and integrating the data are high, and it does not worth the hassle. Second, users were concerned with data sharing and privacy. Third, some people felt uncomfortable looking at the result of their physical activity. Looking at the data make them feel bad or guilty about themselves. Fourth, some users stop using the device because they experienced and/or felt inaccuracy in data and found it unreliable. Fifth, some people felt they have learned enough about their habits and routines after a period of time and did not see any point to continue using the device. Finally, changes in life circumstances made some users abandon their device. Pregnancy, injury and changes in exercise habits were reported as some of the reasons. (Epstein et al., 2016) Table 1 summarizes the reasons discussed in the literature regarding abandonment of wearable devices.

Table 1. Summary of factors behind wearable device abandonment.

	Piwek et al. (2016)	Hänsel et al. (2015)	Salah et al. (2014)	Schrager et al. (2017)	Clawson et al. (2015)	Harrison et al. (2015)	Lazar et al. (2015)	Epstein et al. (2016)
Poor User Interface Design		✓					✓	
Poor User Experience Design	✓	✓					✓	
Data Inaccuracy	✓		✓	✓		✓		✓
Discomfort			✓	✓		✓	✓	
Unfashionable			✓	✓		✓		
Social Awkwardness			✓					
Social Switching					✓	✓		
Interest Lost				✓				
Malfunction				✓				
Goal Achievement					✓			
Device Upgrade					✓			
Illness & Physical Limitation					✓			✓
Feeling of Shame and/or Guilt								✓
Needs and Device Capabilities Mismatch					✓		✓	✓
Incompatibility						✓		
Usage Effort & Device Maintenance							✓	✓
Data Privacy								✓

As it can be seen from the above table, the most common reasons for abandonment of wearables are data inaccuracy and discomfort. In addition, poor user interface design, poor user experience design, being unfashionable and mismatch between needs and device capabilities are also mentioned in several papers.

This section gave an overview of wearables, why consumers use them and factors behind low retention rates. The following section will discuss motivation and human behavior by first defining motivation and then introducing few well-known theories and models of motivation and human behavior.

2.2 Motivation and Human Behavior

2.2.1 Motivation

Nevid (2011) defined motivation as “factors that activate, direct, and sustain goal directed behavior” (p. 280). Motives are, the needs and wants which drive behavior, explaining why we do what we do. Motivation can be categorized further into intrinsic and extrinsic motivation.

As the name implies, intrinsic motivation comes from internal interest and enjoyment while extrinsic motivation is generated by external influences and rewards (Ryan & Deci, 2000). Studies have shown that goals and aspirations with intrinsic motives lead to greater health, well-being and performance in comparison with extrinsic motives (Deci & Ryan, 2008).

2.2.2 Maslow Hierarchy of Needs

Human motivation is mainly coming from two types of needs: biological and psychological. Maslow (1943) divided these biological and psychological needs into five levels and arranged them in a hierarchy (Figure 2). These levels from bottom to top are: (1) physiological needs such as hunger; (2) safety needs such as secure housing; (3) love and belongingness needs such as friendship; (4) esteem needs such as respect; (5) self-actualization needs which is fulfilling one's potential. Arranging these needs in a hierarchy means that an individual is motivated to fulfill basic needs (at a satisfactory degree) first before moving upward in the hierarchy. (Maslow, 1943)

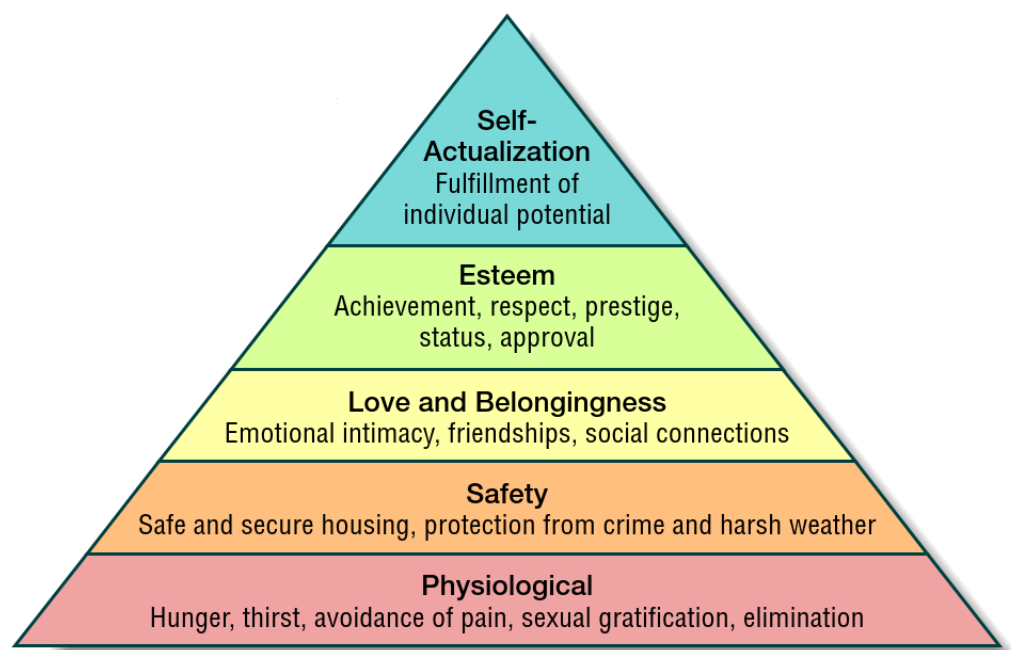


Figure 2. Maslow hierarchy of needs (Adapted from Nevid, 2011, p. 285).

2.2.3 Self-Determination Theory (SDT)

Self-Determination Theory (SDT) is a popular theory of motivation introduced by Richard Ryan and Edward Deci. This theory states that the degree to which an activity is intrinsically motivating depends on how much it supports three basic psychological needs: autonomy, competence, and relatedness (Ryan & Deci, 2002). These needs are universal and satisfaction of them are required for effective functioning and psychological health & wellbeing (Deci & Ryan, 2008). Autonomy refers to human's need to be in

control of actions and have a sense of choice. Competence is the feeling of effectiveness in overcoming challenges and building skills. Relatedness refers to the need to feel connected and accepted by others. (Rupp et al., 2016)

Based on the self-determination theory, motivation can be divided to three types: autonomous motivation, controlled motivation and amotivation. Autonomous motivation is the most self-determined. Autonomous motivation is the result of ongoing satisfaction of all three basic psychological needs. Therefore, it is the outcome of personal interests and/or personal values. Controlled motivation is the result of some satisfaction in competence and relatedness needs but dissatisfaction in the need for autonomy. Controlled motivation is usually a combination of introjected regulation and external regulation. This means that individual becomes motivated in an activity or behavior to avoid guilt, obtain social approval, avoid punishment or obtain a reward. Finally, amotivation is when an individual neither have internal nor external motivation to engage in an activity or behavior. (Deci & Ryan, 2008; Kerner & Goodyear, 2017)

2.2.4 Self-efficacy

Self-efficacy is another widely discussed concept when investigating health promoting and healthy behavior. Self-efficacy refers to an individual's belief that he/she can take control over his/her motivation, behavior and social environment (Bandura, 1990). People with strong sense of self-efficacy tend to form and maintain a strong commitment to tasks and persist in challenging situations. On the other hand, people with the weak sense of self-efficacy tend to avoid difficult tasks and challenging situations. (Hänsel et al., 2015)

According to Stajkovic & Luthans (1998), there are four determinants of self-efficacy: enactive mastery experiences, vicarious learning, verbal persuasion and psychological arousal. Enactive master experiences refers to the fact that succeeding in perceived challenging tasks can result to an increase in self-efficacy. Vicarious learning means that individuals' self-efficacy increases when they see a role model or a person that they perceive competent performs and accomplishes a task. The greater perceived similarity between an individual and the role model in terms of characteristics required for completing a task or performing a behavior, the more likely the individual feels stronger self-efficacy in performing the task or behavior. Verbal persuasion refers to impact on receiving compliments from perceived competent people in increasing an individual's self-efficacy. Finally, the state of the psychological and emotional arousal impacts on self-efficacy. For example, people with strong self-efficacy may see the psychological arousal as an energizer while it has opposite effect on people with weak self-efficacy. (Stajkovic & Luthans, 1998)

2.2.5 Theory of Reasoned Action (TRA)

The theory of reasoned action (TRA) is a model from social psychology to explain determinants of consciously intended behaviors. TRA argues that a person's performance of a behavior is determined by his/her behavioral intention, i.e., the strength of a person's intention to do a specific behavior. Behavioral intention (BI) is determined by attitude toward behavior and subjective norm. (Davis et al., 1989) Figure 3 illustrates the theory of reasoned action.

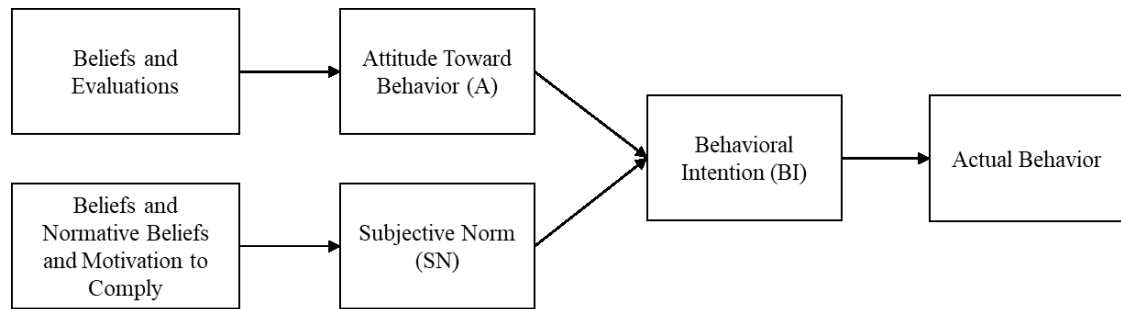


Figure 3. Theory of Reasoned Action (Adapted from Davis et al., 1989, p. 984).

Attitude towards the behavior (A) is the person's feeling (positive or negative) about that specific behavior which is measured based on multiplication of a person's perceived beliefs about consequences of the behavior by evaluation of those consequences. Subjective norm (SN) is the perception of the person about what most people who are important to him/her think should be done regarding that specific behavior. SN is evaluated based on the multiplication of a person's normative beliefs by his/her motivation to comply with other's expectations. TRA is a general model, so it does not specifically mention the beliefs that are operative for a particular behavior. (Davis et al., 1989) Researchers developed several other models and theories based on the theory of reasoned behavior such as the theory of planned behavior (TPB) and the technology acceptance model (TAM).

2.3 Technology Adoption

2.3.1 Technology Acceptance Model (TAM)

The technology acceptance model (TAM) is a tailored version of TRA for the purpose of modeling user acceptance of information systems. The main goal of TAM is to provide determinants of computer acceptance in a way that it can explain user behavior across a wide range of end-user computing technologies and user populations. In addition, TAM is aiming for tracking the impact of external factors on internal beliefs, attitudes and intentions. (Davis et al., 1989) Figure 4 demonstrates technology acceptance model (TAM).

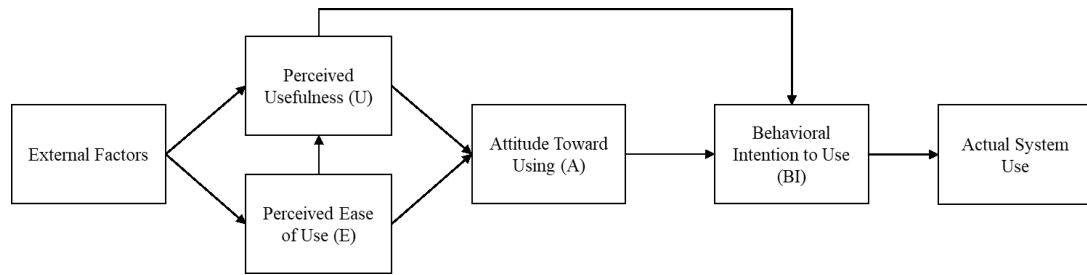


Figure 4. Technology Acceptance Model (Adapted from Davis et al., 1989, p. 985).

Similar to TRA, TAM argues that actual system use is determined by behavioral intention to use (BI). Behavioral intention is based on the attitude toward using (A) and also influenced directly by perceived usefulness (U). Perceived usefulness is an individual's subjective perception that a specific application system will increase his/her performance. Attitude toward using is determined by perceived ease of use (E) and perceived usefulness. Perceived ease of use is the degree to which an individual expects the target system to be free of effort. That is why in addition to attitude toward using, it also directly impacts on perceived usefulness. Finally, both perceived usefulness and perceived ease of use are determined by external variables such as accuracy, aesthetics, documentation, training, user support and system features. (Davis et al., 1989)

Several extensions and/or modified versions of TAM model have been introduced from which TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008) are the notable ones. Further discussion about TAM2 and TAM3 is out of scope of this thesis. This section continues by discussing another model called the unified theory of acceptance and use of technology (UTAUT) which is partly based on TAM model as well.

2.3.2 Unified Theory of Acceptance and Use of Technology

In the past few decades, scholars have developed several competing models for acceptance of computer and information technology. Venkatesh et al. (2003) selected and reviewed eight prominent models. The eight selected models were the theory of reasoned action, the technology acceptance model, the motivational model, the theory of planned behavior, a model combining the technology acceptance model and the theory of planned behavior, the model of PC utilization, the innovation diffusion theory, and the social cognitive theory. Based on these eight models, they formulated a unified model (Figure 5) called the unified theory of acceptance and use of technology (UTAUT) which integrates elements across all these models. After conducting an empirical study, authors reached the conclusion that UTAUT model outperformed the other eight models and could be a good tool for understanding the drivers of technology acceptance and use. (Venkatesh et al., 2003)

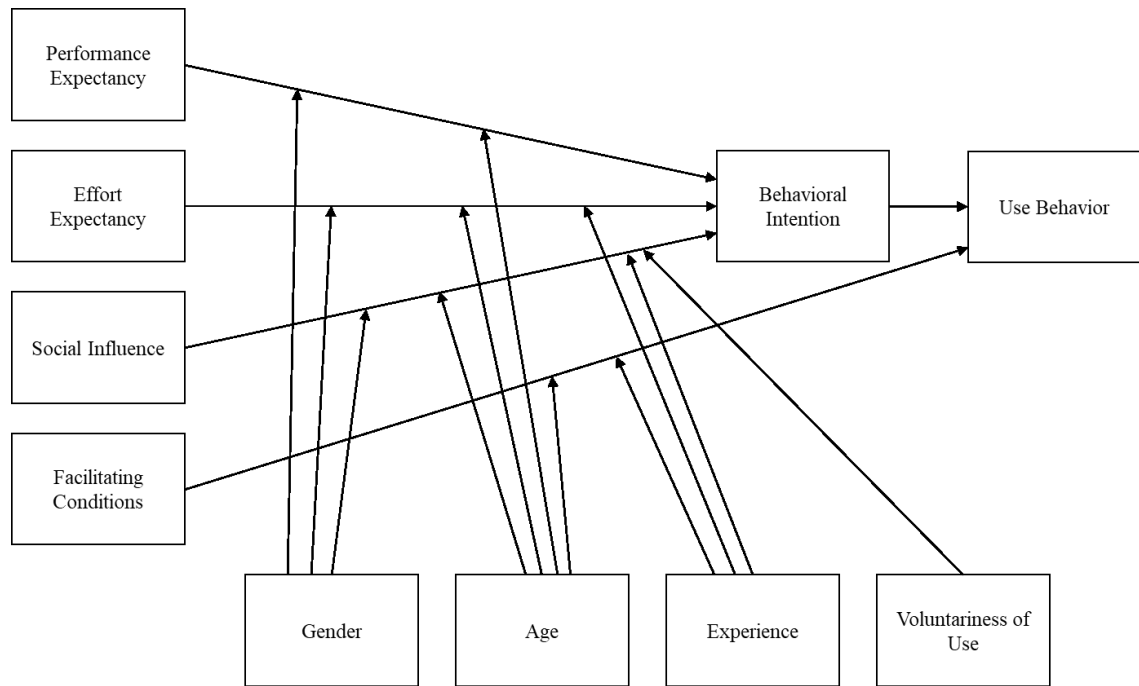


Figure 5. Unified Theory of Acceptance and Use of Technology (Adapted from Venkatesh et al., 2003, p. 447).

Based on UTAUT model, there are four constructs namely performance expectancy, effort expectancy, social influence and facilitating conditions which have a significant role as direct determinants of user acceptance and usage behavior. In addition, there are four key moderators: gender, age, experience and voluntariness of use. (Venkatesh et al., 2003)

Performance expectancy is the degree that an individual perceives gains in a job/task by using the system. Performance expectancy is a determinant of behavioral intention, and the strength of the impact varies with gender and age. In an organizational setting, it appears that the impact of performance expectancy on intention is more significant for men and younger workers. Effort expectancy is the degree to which use of the system is perceived easy. Three moderators (gender, age and experience) impact on the strength of relationship between effort expectancy and intention. In an organizational setting, the impact is stronger for women, older workers and people with limited experience. Social influence is the degree that opinions of important others in using the system determines intention to use. All four moderators impact the relationship between social influence and intention. In the organization setting, the impact is stronger for women, older workers, for people with limited experience and if it is mandatory to use the system. Facilitating conditions is the degree that an individual perceives the availability of organizational and technical infrastructure to use the system. The relationship between facilitating conditions and use behavior is stronger for older workers with increasing experience. In other words, older workers with more experience tend to request more help and assistance in using the system. (Venkatesh et al., 2003)

2.3.3 Unified Theory of Acceptance and Use of Technology 2

UTAUT primarily focuses on factors related to behavioral intention to use a technology in an organizational context. In 2012, Venkatesh et al. introduced a modified version of this model and called it UTAUT2, which is a tailored version of UTAUT to be suitable for consumer context. In UTAUT2, three new constructs are added to the four constructs mentioned in UTAUT and definitions of the constructs are slightly modified to be more suitable for the consumer context. In addition, one of the moderators (voluntariness of use) is removed since in majority of cases consumers' behavior is voluntary unlike in organizations. (Venkatesh et al., 2012) Figure 6 demonstrates UTAUT2 model.

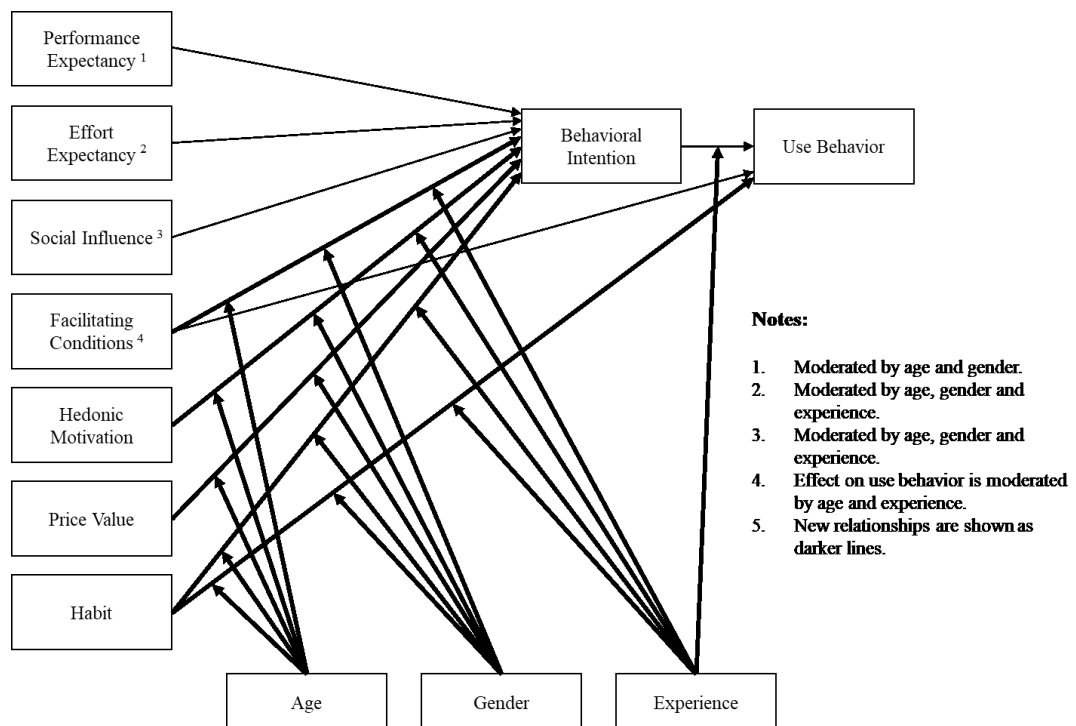


Figure 6. UTAUT2 model (Adapted from Venkatesh et al., 2012, p. 160).

In this model, performance expectancy is defined as the degree using a technology will benefit consumers in doing certain activities. Effort expectancy is ease of using a technology from consumers' point of view. Social influence is the degree that consumers get influenced by others (e.g. family and friends) in using a technology. Facilitating conditions is the perception of consumers about availability of resources and support to perform a behavior. Hedonic motivation is the enjoyment and pleasure gained from using a technology. Price value refers to the tradeoff between perceived benefits and perceived costs of the technology. Price value is positive if benefits perceived from a technology outweigh perceived costs of the technology. Habit is the extent to which people conduct behavior automatically due to past learning. (Venkatesh et al., 2012)

Facilitating conditions are moderated by age, gender and experience. Younger individuals tend to require less instructions than older ones. Men on average are willing to spend more time to overcome constraints so they rely less on facilitating conditions. Finally, individuals who are more familiar with the technology rely less on facilitating conditions. Hedonic motivation is moderated by age, gender and experience because consumers have different novelty seeking and perceptions of novelty of the targeted technology. When consumers start using a technology, they pay more attention to its novelty, i.e., unique features, interfaces and so on. But as experience of using a certain technology increases, novelty slowly loses its value and is replaced by things such as efficiency and effectiveness. Age and gender also influence on hedonic motivation in a way that younger men have a stronger tendency towards technology innovativeness. The price is moderated mainly by age and gender. Women tend to pay more attention to the price and are more conscious about it. In addition, older consumers especially older women are usually more price-sensitive due to their social role as family expenditure gatekeepers. Habit is moderated by age, gender and experience. Older consumers tend to rely more on their habit in guiding their intention and use behavior. In addition, men tend to rely more heavily on their habit especially when they have high level of experience with the technology. (Venkatesh et al., 2012)

2.4 Individual's Adoption to Wearables

In the previous sections, an overview of wearable technologies was given, and some motivation theories and technology acceptance models were discussed. This section reviews several studies done on factors influencing individual's adoption to wearables.

Gu et al. (2016) conducted a study to explore factors influencing on consumers' initial trust in the wearable commerce. They propose a conceptual model based on UTAUT2 and achievements in the mobile commerce (Figure 7). To test the conceptual model, they conducted an empirical study using questionnaire survey both online and offline. Survey participants were undergraduate and graduate students and some young IT workers. Data collected for this study was from 266 questionnaires. Result of this study showed that the initial trust has a strong impact on use intention. Initial trust is influenced by five factors. Performance expectancy, facilitating conditions and hedonic motivation all showed the positive influence on initial trust. Privacy concern could have negative influence on the trust. Result of the study showed that privacy concerns varied among participants and it was to some degree impacted by the level of education and the familiarity with wearable technology. Finally, trust propensity has a significant impact on the initial trust. Results of the study showed that the effect of consumer personality factors on wearable commerce is very large. (Gu et al., 2016)

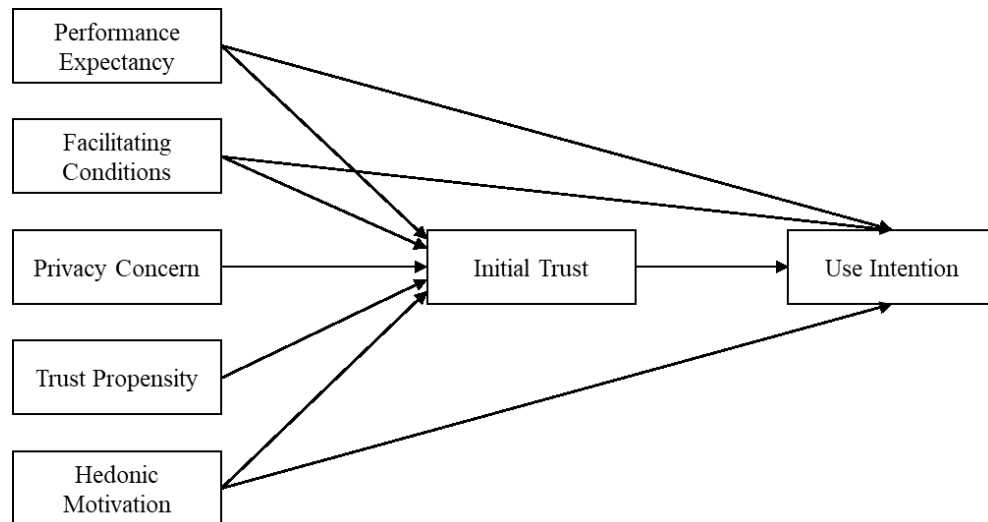


Figure 7. Conceptual model for initial trust of wearable commerce (Adapted from Gu et al., 2016, p. 80).

Lunney et al. (2016), conducted a study to gain a better understanding on how and why people are using wearable devices and what is the impact of wearables on their health. This study mainly focuses on wearable fitness trackers or shortly WFTs. The model used in this study (Figure 8) is constructed based on variables from TAM model (perceived usefulness and perceived ease of use) and TBP (subjective norm and attitude). Empirical data of the study was collected via an online survey in the United States with 206 participants. The results of this study showed that the perceived usefulness and the perceived ease of use have a significant influence on the adoption and use of wearables. Subjective norm has a strong influence on WFT use. Therefore, authors believe that using social gamification such as social media sharing and linking fitness data with friend and family (ex. Leaderboards) will help to keep the user motivated. Finally, this study concludes that there is a positive relationship between WFT use and perceived health benefits including perceived health improvement and active lifestyle. (Lunney et al., 2016)

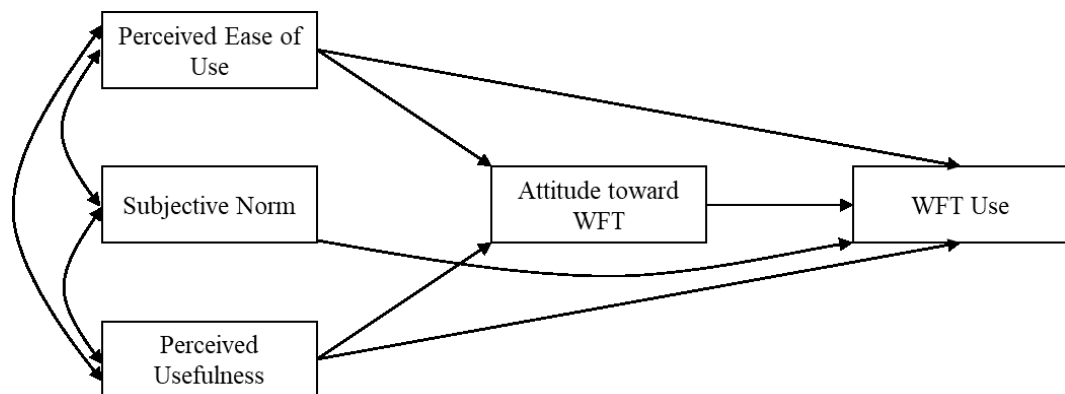


Figure 8. Wearable fitness tracking adoption and use model (Adapted from Lunney et al., 2016, p. 177).

Yang et al. (2016) did a study to analyze customers' perceived value of wearable devices. For the purpose of this study, they developed a research model illustrated in Figure 9. This model proposes a comprehensive framework for investigating factors impacting on perceived value of wearable devices. Empirical data was collected via online survey in South Korea. 375 people participated in this study from which 273 were potential users and 102 actual users of wearable devices. The results of this study showed that perceived value has a significant impact on both potential and actual users' intention to use. Overall, impact of perceived benefits is stronger than perceived risks meaning participants valued positive aspects of wearable devices more than they were concerned about the risks. In addition, this study revealed that perceived risks are only important for potential users and not actual users. (Yang et al., 2016)

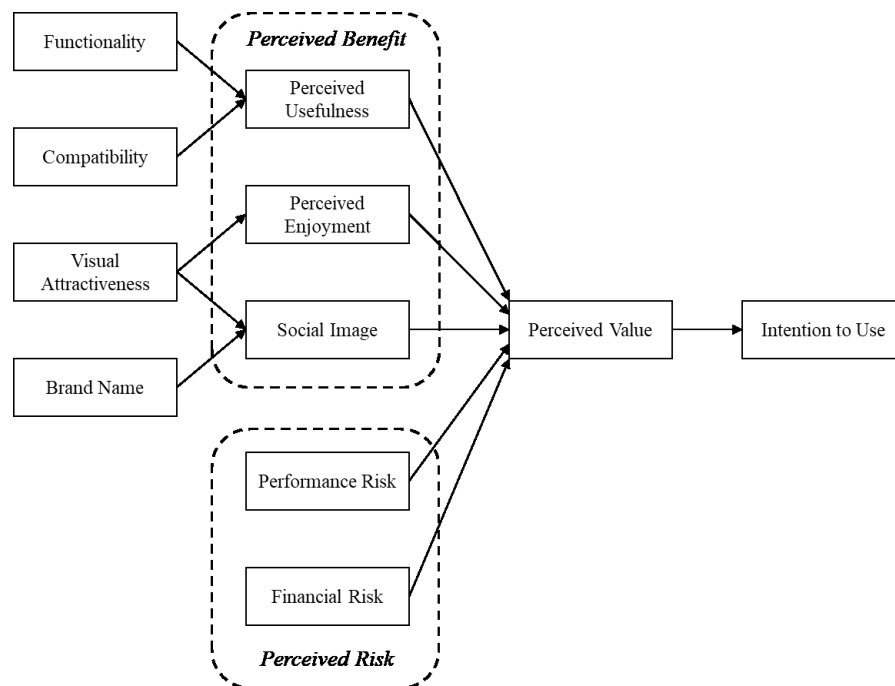


Figure 9. Framework for investigating factors impacting on perceived value of wearable devices (Adapted from Yang et al., 2016, p. 258).

Gao et al. (2015) performed a study to investigate factors associated with a consumer's intention to adopt wearable technology in healthcare and to explore moderating effects of the product type on adoption intention. They developed a model based on UTAUT2, the protection motivation theory and the privacy calculus theory (Figure 10). The empirical data of this study was collected via survey for a total of 462 participants. This study revealed that all factors presented in the model have significant impact on a consumer's decision to adopt to a wearable technology. Moreover, this study showed that there is a difference between the acceptance of product types (i.e., fitness wearables and medical wearables). Fitness wearable users pay attention to factors such as social influence, hedonic motivation, functional congruence, perceived privacy risk and perceived

vulnerability. While, users of medical wearables care more about factors including effort expectancy, perceived expectancy, self-efficacy and perceived severity.

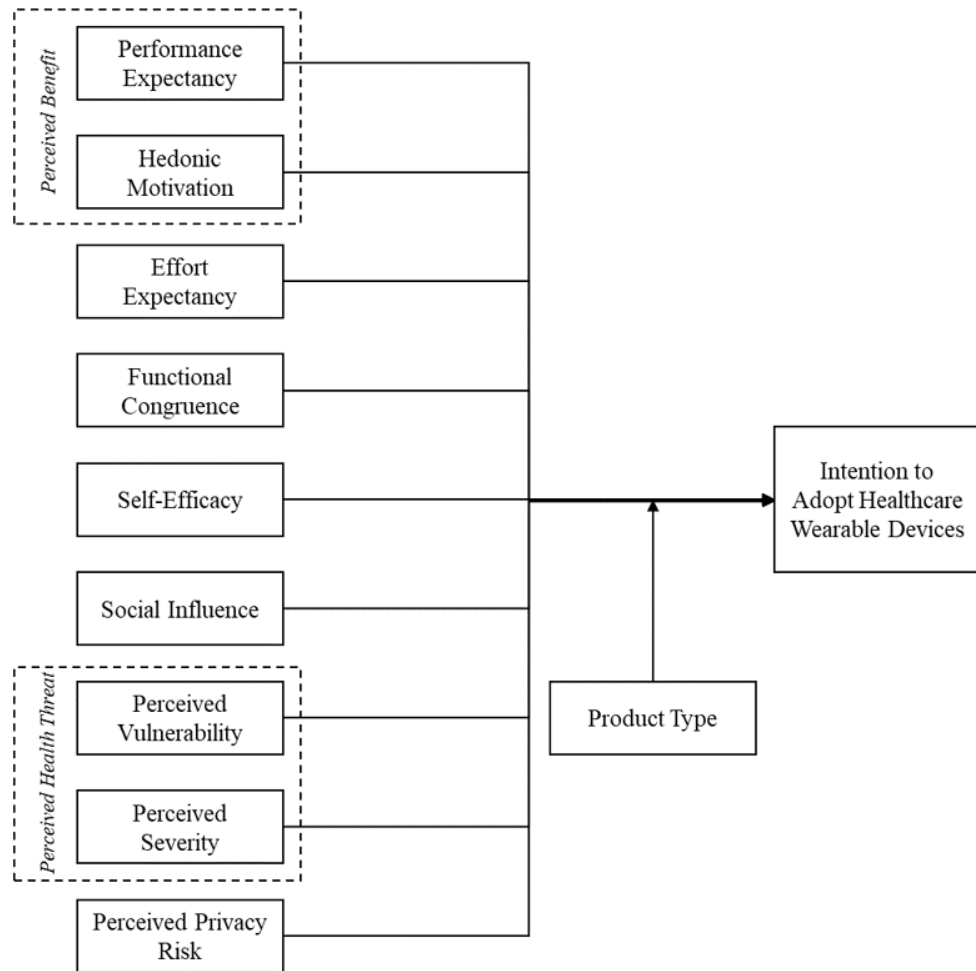


Figure 10. Factors associated with consumer's intention to adopt wearable technology in healthcare (Adapted from Gao et al., 2015, p. 1707).

Kim & Shin (2015) conducted a study to identify main psychological determinants of the smart watch adoption. They developed a model based on TAM. In their proposed model, they argued that perceived usefulness is positively affected by the affective quality (AQ) and the relative advantage (RA). Affective quality is “the degree to which users believe that a stimulus can change one’s core affect (i.e. mood, emotion, feelings)”, which will consequently determine a person’s perceptions and behaviors. The relative advantage means that a certain technology is adopted faster if it is perceived to be better than comparable technologies. In addition, the proposed model suggests that perceived ease of use is positively impacted by mobility (MB) and availability (AV). Mobility is the degree that users believe their device can be used during transit from one location to another. Availability refers to the user’s perception about the device real-time connectivity to information and services. Kim & Shin (2015) also added the subcultural appeal and the cost to TAM. Subcultural appeal means the degree that using a technology distinguishes

users from most people. Subcultural appeal has positive impact on attitudes towards the use. Finally, the perceived cost of the technology negatively impacts on the intention to use. The empirical data of the study was collected through online survey with 363 participants. Result of the empirical study supported the proposed research model. (Kim & Shin, 2015) Figure 11 demonstrates smart watch adoption model.

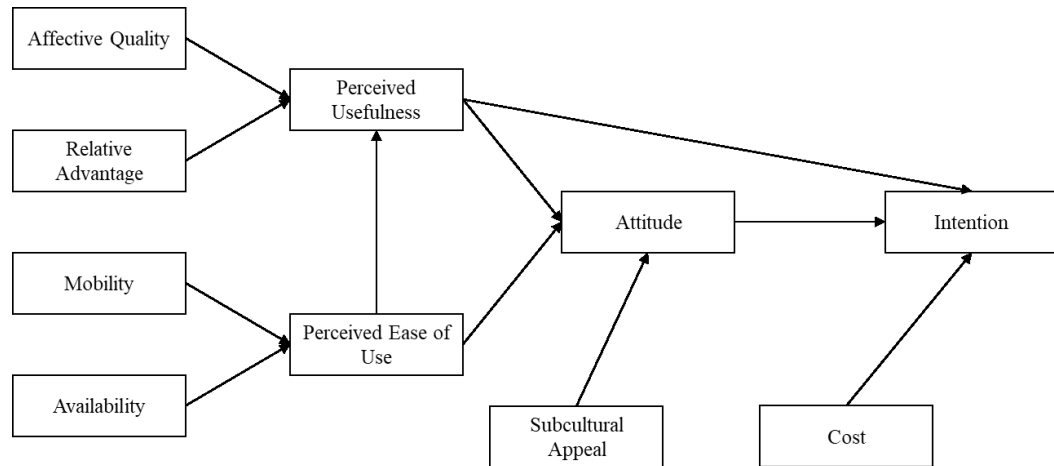


Figure 11. Smart watch adoption model (Adapted from Kim & Shin 2015, p. 534).

Kalantari (2017) conducted a study reviewing and synthesizing literature of consumers' adoption of wearable technologies. Author reviewed 50 papers which studied factors influencing on the adoption and the diffusion of wearable technologies. Afterwards authors grouped these factors into five categories as it can be seen in Figure 12. Perceived benefits consist of four factors namely perceived usefulness, perceived ease-of-use, perceived value and perceived enjoyment. All these factors are already defined in previous sections. Technology characteristics includes perceived quality, perceived aesthetics, perceived comfort, perceived compatibility and visibility. Perceived quality is a consumer's overall perception of the quality of the product which is closely related to the product brand image. Perceived aesthetics refer to attributes such as design, form, color and texture of the device. Perceived comfort refers to attributes such as weight, flexibility and elasticity. Perceived compatibility can be defined as "the degree to which wearable devices comply with other products' technical functionalities, users' business needs and lifestyles". Finally, visibility means the degree to which technology is noticed by other people. (Kalantari, 2017)

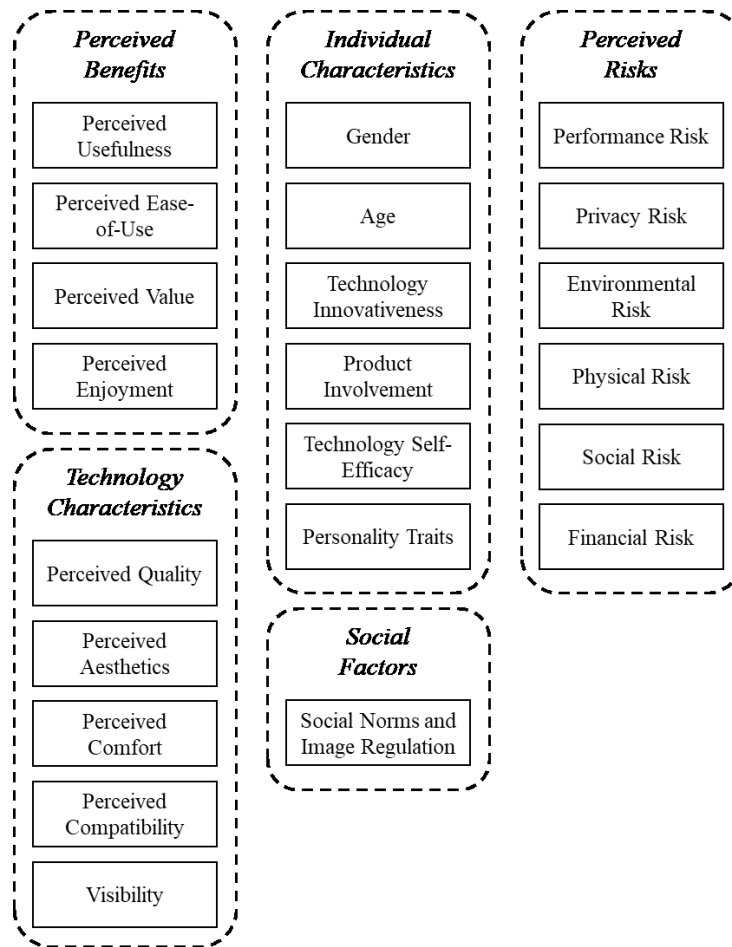


Figure 12. Factors influencing the adoption of wearable technologies (Adapted from Kalantari, 2017, p. 299).

Individual characteristics consists of gender, age, technology innovativeness, product involvement, technology self-efficacy and personality traits. Gender, age, technology self-efficacy and personality traits are self-explanatory or already discussed in previous sections. Technology innovativeness means users tendency to take risk and try out an innovation. Product involvement refers to the degree that an individual perceives the product to be personally relevant to them. Social factors include social norms and image regulations which means how the technology helps an individual to improve their social image, express themselves and differentiate from others. Perceived risks consist of performance risk, privacy risk, environmental risk, physical risk, social risk and financial risks. Performance risk is a consumer's concern that performance of the technology is not as they expected. Privacy risk refers to trustworthiness of the technology in handling data in safe and secure manner. Environmental risk refers to potential impacts the technology have on the environment. Physical risk means potential negative impacts of using a technology on their health and well-being. Social risk is about evaluation of consumer's social group in adoption and use decision. Financial risks are net financial loss due to money spent to buy a device and possibility of repairing, replacing or refunding. (Kalantari, 2017)

2.5 Research Framework of the Study

Based on the technology adoption theories and the literature review on factors influencing individual's adoption to wearables, a new model is proposed which can be seen in Figure 13. Based on this model, a consumer's intention to use a wearable device is dependent on perceived value. Perceived value is the "customer's overall assessment of the utility of a product based on perceptions of what is received and what is given" (Zeithaml, 1988, p. 14).

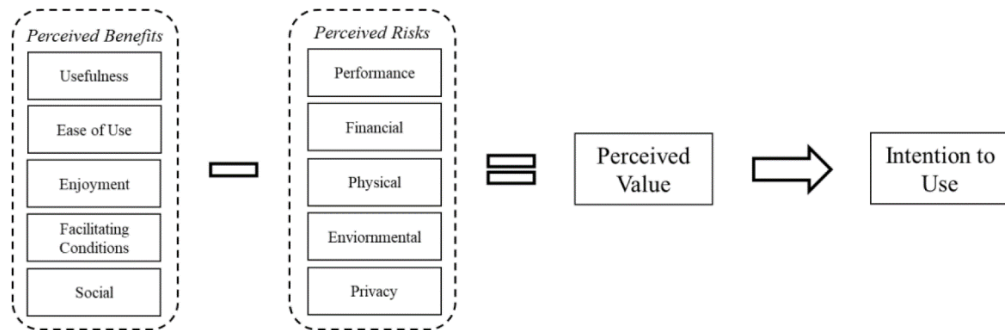


Figure 13. Factors influencing individual's adoption to wearables.

Five factors determine perceived benefits: usefulness, ease of use, enjoyment, facilitating conditions and social. And five factors determine perceived risks: performance, financial, physical, environmental and privacy. Table 2 lists all the factors, their definition and sources.

Table 2. Definition and sources of factors behind influencing individual's adoption to wearables.

	Factors	Definition	Sources
Perceived Benefits	Usefulness	Individual's subjective perception that a specific application system will increase his/her performance. (Also referred to as performance expectancy)	Gu et al. (2016), Kalantari (2017), Lunney et al. (2016), Yang et al. (2016), Gao et al. (2015), Kim & Shin (2015)
	Ease of Use	The degree to which an individual expects the target system to be free of effort. (Also referred to as effort expectancy)	Gu et al. (2016), Kalantari (2017), Lunney et al. (2016), Gao et al. (2015), Kim & Shin (2015)
	Enjoyment	Pleasure gained from using a technology. (Also referred to as hedonic motivation)	Gu et al. (2016), Kalantari (2017), Yang et al. (2016), Gao et al. (2015)
	Facilitating Conditions	Perception of consumers about availability of resources and support to perform a behavior	Gu et al. (2016)
	Social	How the technology helps an individual to improve their social image, express themselves and differentiate from others. (Also referred to as subcultural appeal)	Gu et al. (2016), Kalantari (2017), Yang et al. (2016), Gao et al. (2015), Kim & Shin (2015)

Perceived Risks	Performance	Individual's concern that performance of the technology is not as expected	Kalantari (2017), Yang et al. (2016)
	Financial	Net financial loss due to technology cost and possibility of repairing, replacing or refunding. (Also referred to as cost)	Kalantari (2017), Yang et al. (2016), Kim & Shin (2015)
	Physical	Potential negative impacts of using a technology on their health and well-being	Kalantari (2017)
	Environmental	Potential negative impacts on the technology on the environment	Kalantari (2017)
	Privacy	Trustworthiness of the technology in handling data in safe and secure manner	Kalantari (2017), Gao et al. (2015)

Even though moderating factors such as age, gender and personality have impact on the significance of perceived benefits and risks factors, investigating their impacts is out of the scope of this thesis. Therefore, they are excluded from the model presented in Figure 13.

In Section 2.4.1 literature related to the abandonment of wearable technologies were reviewed and as it can be seen in Table 1, seventeen factors were found for the abandonment of wearable devices. Many of these factors are closely related to the other factors and can be grouped together. As a result, a new categorization is presented in Figure 14 by combining and synthesizing the literature review findings.

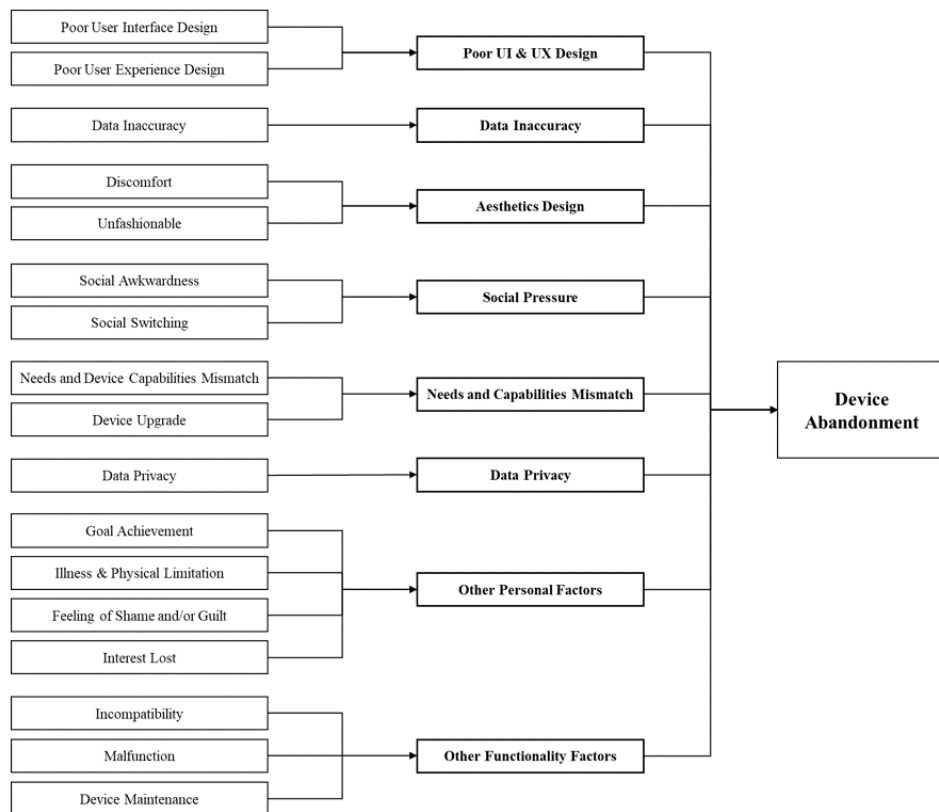


Figure 14. New categorization for factors behind wearable device abandonment.

Poor user interface and user experience design factors are combined, because these factors are closely related. Data inaccuracy mentioned many times in reviewed articles as one of the key reasons behind abandonment. So, it is kept as its own category. Discomfort and unfashionable are combined to a new group called aesthetic design. Social pressure is a combination of social awkwardness caused by device features and social switching which is related to abandoning the device due to recommendations of others or to fit better in social group.

Device upgrade and mismatch of needs and device capabilities are combined to one group since they arise from similar needs. Data privacy has its own standalone category since it is not closely related to any other factors. Other personal factors is a combination of all factors such as illness, individual's feelings, goal achievement and interest lost. All these factors are heavily related to the person's condition, life circumstances and personality. Finally, other functionality factors category is a combination of variety of functionality related reasons such as incompatibility with other devices, device malfunction. Battery life, device maintenance and so on.

The main goal of this thesis is to investigate factors influencing a consumer's adoption and use of wearable technologies. Figure 13 demonstrated factors behind consumer's adoption to wearable devices. While Figure 14 provided factors behind wearable device abandonment. Combining these two figures provides a theoretical framework to address the objective of this thesis (Figure 15).

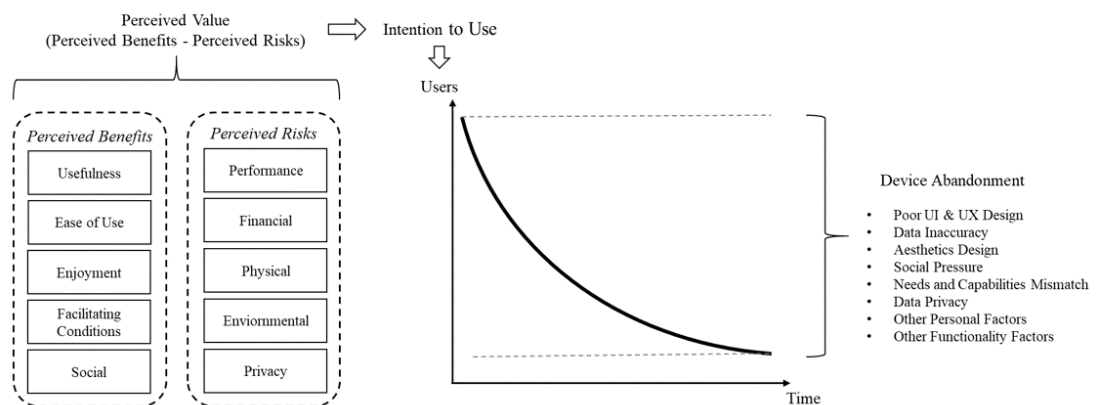


Figure 15. Theoretical framework of the thesis.

As it can be seen in above figure, a consumer's intention to use depends on the tradeoff between perceived benefits of wearable device and perceived risks. If perceived benefits overpass perceived risks, it affects positively on a consumer's intention to use and becoming a user. Over time more and more users start abandoning the device due to one or several factors such as poor UI & UX design, data inaccuracy and aesthetic design.

In this chapter, a theoretical framework was introduced to demonstrate factors influencing on consumers' adoption, use and abandonment of wearable devices. This theoretical framework was constructed based on reviewing literature about adoption, use and effectiveness of wearable technologies. Next chapter will go through research design and methods used for collecting and analyzing empirical data of this thesis.

3. Research Design and Methods

3.1 Research Methodology

According to Remenyi et al. (1998), research methodology is a procedural framework for conducting a research. Research methodology is selected based on the research topic and research questions. From one perspective, research can be categorized into theoretical research and empirical research. Theoretical research focuses on reviewing existing literature in order to provide answers to research questions, construct theoretical framework and so on (Remenyi et al., 1998). While empirical research also gathers and analyzes empirical data and reports the findings (Minor et al., 1994). Empirical data can be gathered quantitatively or qualitatively (Moody, 2002). However, it is also common to use combination of both quantitative and qualitative methods.

This thesis is an empirical study and uses netnography method to gather empirical data. “Netnography or ethnography on the internet, is a new qualitative research methodology that adapts ethnographic research techniques to the study of cultures and communities emerging through computer-mediated communications” (Kozinets, 2002, p. 2). According to Kozinets (2002), netnography provides several benefits from which two stand out. First, in comparison to traditional ethnography, it is cheaper and less time consuming. Second, netnography is far less obtrusive than some other methods such as focus groups and interviews. As a result, it is possible to collect data from conversations and discussions which occurred naturally. Kozinets (2010) provided a simplified flow of a netnography research project illustrated in Figure 16.

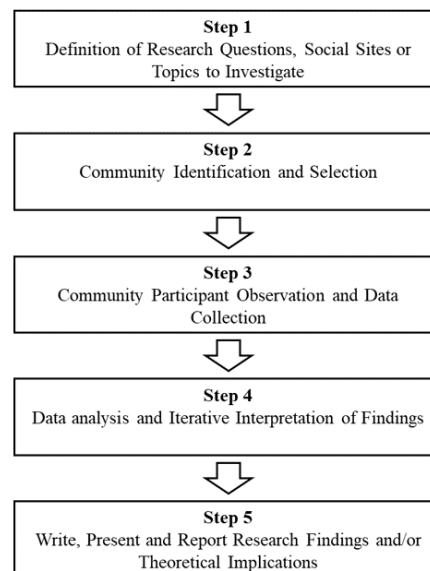


Figure 16. Simplified flow of a netnography research project (Adapted from Kozinets 2010, p. 61)

This thesis follows five steps mentioned in the above figure. The first four steps will be covered in the remaining sections of this chapter and the fifth step will be covered in detail in the next chapter.

3.2 Research Questions

The main objective of this thesis is to investigate factors influencing consumers' adoption and use of wearable technologies. On one hand, it is important to understand why consumers adopt and start using wearable technologies. On the other hand, it is essential to explore the reasoning behind the abandonment of wearable technologies after a period of time. Therefore, two research questions are formed to address the objective of this thesis:

RQ1: What are the factors behind consumer decision to acquire and use a wearable device?

RQ2: Why retention rate of wearable devices is low?

Research question one aims to understand consumers decision making process and reasoning behind adopting and using a wearable device. After reviewing literature related to human behavior and technology adoption, a theoretical model (Figure 13) was built. This model suggests that intention to adopt and use of a wearable technology is affected by the consumer's perceived value. If perceived benefits of a wearable technology overpasses perceived risks, then the consumer decides to adopt and use the wearable device. In the proposed model, five factors were suggested which influence perceived benefits. These factors are: usefulness, ease of use, enjoyment, facilitating conditions, social. Also, five factors were suggested which impact on perceived risks. These factors are: performance, financial, physical, environment and privacy.

Research question two aims to understand why high percentage of consumers abandon their wearable device after a relatively short period of time. For this purpose, literature related to the use and the abandonment of wearable technologies reviewed in the previous chapter and factors behind the wearable device abandonment found and recategorized (Figure 14). It is suggested that there are eight factors which are behind abandonment of wearable devices. These factors are: Poor UI and UX design, data inaccuracy, aesthetic design, social pressure, needs and capabilities mismatch, data privacy, other personal factors and other functionality factors.

3.3 Online Community Selection

After research questions were identified, it was time to find and select suitable online communities. For the purpose of this thesis, several online communities were identified. These communities were: the product review section of e-commerce platforms such as

Amazon, online forums and threads such as ones available in Reddit, social media pages such as Facebook groups, platforms for selling second hand devices such as Craigslist and specialized websites for reviewing wearable technologies.




According to Kozinets (2002), online communities which have one or several of the following criteria are preferred and should be selected for data collection purposes. First, online communities which have strong focus on areas relevant to identified research questions. Second, there is a high traffic of posts. Third, there is a large number of people who participate in the discussion. Fourth, there are detailed and rich posts/data available. Finally, there is a sufficient number of interactions between members of the online community which are relevant to the research questions. (Kozinets, 2002)

Based on the mentioned criteria, Amazon was selected as the most suitable online community for the purpose of this thesis. Amazon is a well-established e-commerce platform. Almost all wearable devices relevant for the purpose of this study can be found there. Due to the large number of people who write reviews about products (such as wearable devices), many product reviews are available from which sufficient number are very detailed and rich. Even though there is not much active discussion in Amazon, there is an option to filter top rated reviews. Top rated reviews are usually very insightful and detailed, focusing on one or several aspects of the product. They are labeled as top rated because tens or even hundreds of other consumers voted them as insightful (useful) which gives extra credibility to the top rated reviews.

3.4 Data Collection Method

The first step of data collection was to narrow down the product selection, so data collection is manageable for the scope of this thesis. As mentioned at the end of the section 2.1.1, this thesis focuses on the consumer market segment and only on trackers category. There is a wide range of trackers available in the market with different specifications, designs and prices. Five criteria were set in order to facilitate the selection process. First, it was decided to select three trackers from different brands, so the data is not limited to only one brand or model. Second, all trackers should have similar (almost similar) specifications. Third, trackers should belong to price range of 50 to 200 Dollars, so they offer wide range of functionalities and at the same time still affordable for many people. Fourth, trackers are from well-known brands so sufficient number of customer reviews can be found in Amazon. Finally, trackers have been in the market at least for one year so there are enough consumers who adopted and used the products. Based on these criteria, three trackers were selected: Fitbit Charge 2, Garmin Vivosmart HR+ and Polar A370. Technical specifications and functionalities of these three devices are listed in Table 3.

Table 3. Technical specifications and functionalities of Fitbit Charge 2, Garmin Vivosmart HR+ and Polar A370.

	Fitbit Charge 2	Garmin Vivosmart HR+	Polar A370
Picture			
Size	Width: 21mm Thickness: 12.7 mm	Width: 21.0 mm Thickness: 15 mm	Width: 23.5 mm Thickness: 13.5 mm
Material	Stainless steel casing, elastomer strap	Silicone	Soft Silicone or Polyurethane (TPU) wristband
Charging	USB	USB	Micro USB
Battery	Lithium battery	Lithium battery	Lithium battery
Battery life	up to 5 days	Up to 5 days watch/activity tracking mode (24/7 heart rate monitoring, no GPS) or up to 8 hours using GPS	Up to 12 hours of training with mobile GPS 4 days of activity tracking with continuous heart rate and 1 h of training per day
Water- resistance	Sweat, rain and splash proof	Up to 50 metres (5 ATM)	WR30
Weight	36 grams	Regular: 31.0 g Large: 33.0 g	Small: 31.7 g Medium/Large: 37.3 g
Sensor	Optical heart rate tracker, 3- axis accelerometer, altimeter, vibration motor	3 axis-accelerometer, altimeter, heart rate monitor, vibration alert, GPS	3d-accelerometer, heart rate monitor
Display	OLED	Touchscreen, 160 x 68 pixels, sunlight-visible, transfective memory-in-pixel (MIP)	Wide-viewing angle full color TFT display with capacitive touchscreen Screen resolution 80 x 160 pixels (RGB)
Screen size	38 mm	25.3 mm x 10.7 mm	13mm x 27mm
Colors	Black, Plum, Blue, Teal, Lavender Rose Gold, Black/Gunmetal	Black, Imperial Purple, Midnight Blue	Available in 6 colors: Black, White, Pink, Violet, Red, Gray
Steps	Yes	Yes	Yes
Distance	Yes	Yes	Yes
Calories burned	Yes	Yes	Yes
Activity	Yes	Yes	Yes
Floors	Yes	Yes	
Sleep	Yes	Yes	Yes
Heart rate	24/7	24/7	24/7
GPS	Connected GPS	Yes	Connected GPS
Other	Guided breathing	Clock, music control, auto goal, move bar	Inactivity alert, Vibration alerts, Alarm, Sport profiles
Smartphone notifications	Yes	Yes	Yes

Data for this study was collected by visiting the official page of these products in Amazon. In the product page, there is a section to find all customer reviews. First customer reviews were sorted out by top rated filter in order to list more detailed and rich reviews (see Appendix A). Then, the first 20 customer reviews from each product were collected (in total 60 customer reviews) and each review was stored separately in a MS Word file. The length of the reviews varies a lot, some reviews are only focusing on one or two aspects, while others evaluate many aspects of the product. Length of all 60 reviews combined is about 15000 words.

3.5 Data Analysis Method

Since the empirical data collected for this thesis is qualitative and in the text format, Atlas.ti was selected for analyzing the data. Atlas.ti is a software used for analyzing wide range of qualitative data such as textual, graphical, audio and video data. The first step for analyzing the data was uploading all the 60 consumer review files to the software and making sure it can be correctly seen and read. Then the consumer review files were categorized to three document groups, so it is easy to link reviews to corresponding products (Figure 17).

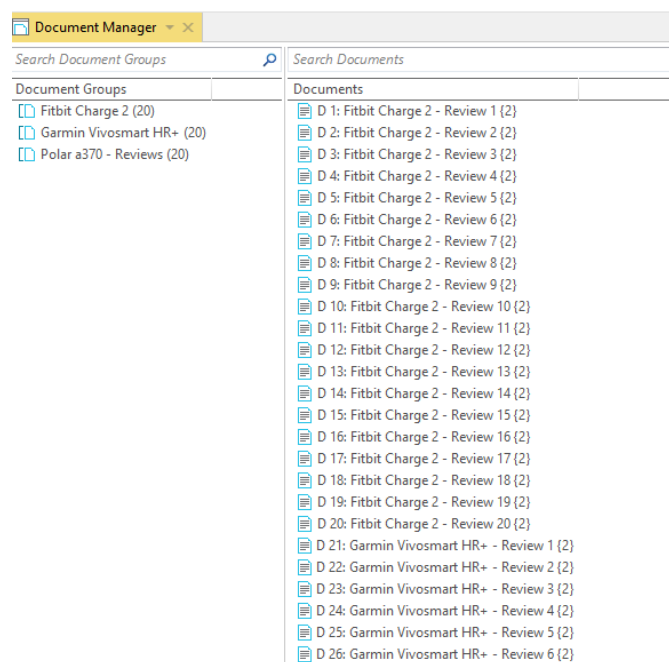


Figure 17. Consumer reviews and document groups.

The collected data was analyzed in two rounds. In the first round, data was analyzed based on two codes: Positive and Negative. Phrases, sentences or paragraphs which were complementing or praising features, functionalities or feel of the product were marked with code “Positive” and the ones which were complaining about features, functionalities or feel of the product were marked with code “Negative”. In the second round of the

analysis, factors identified in the research framework of this thesis (Figure 15) used to guide the coding process. Therefore, phrases, sentences or paragraphs which were coded as “Positive” in the first round of the analysis, coded again based on factors influencing on the consumer’s perceived benefits. In addition, phrases, sentences or paragraphs which were coded as “Negative” in the first round of the analysis, coded again based on factors influencing on the consumer’s perceived risks or the device abandonment. Figure 18 illustrates how the thesis data was coded during the two analysis rounds.

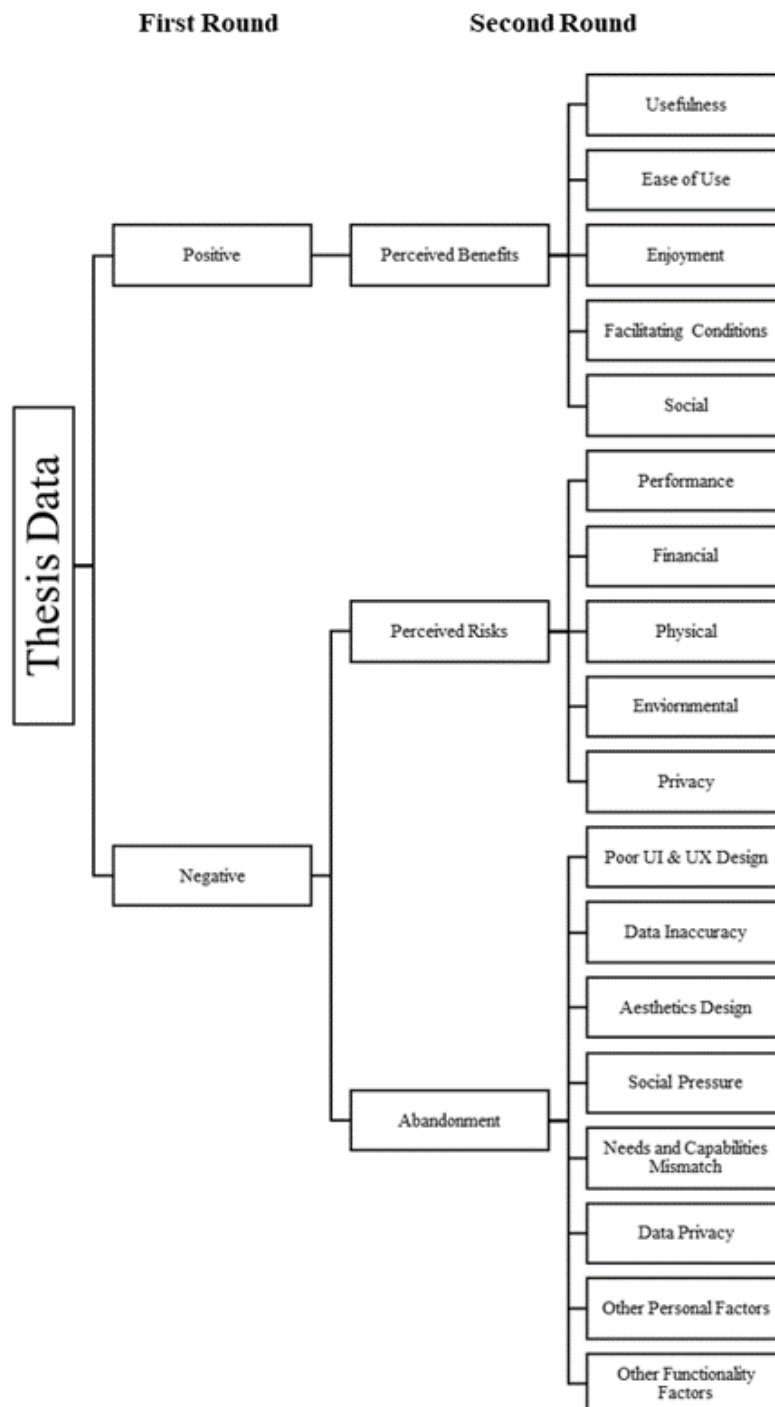


Figure 18. How the thesis data was coded during the two analysis rounds.

It is worth mentioning that, in both rounds of analysis, the data was coded manually. Manual coding was selected over automated coding because automated coding is done by giving software key words or phrases to analyze the data, i.e., the software needs to be instructed on how to analyze the data and what to look for. Even though auto coding is faster, it also increases the chance of missing important insights due to incomprehensive instructions.

After the data was analyzed and coded, Atlas.ti provided the possibility to quantify the data by calculating how frequently each code was used. Quantitative data was used to give an overview on how positively or negatively consumers perceived the fitness trackers and to make a comparison between the selected products. In addition, the quantitative data was an indicator to identify factors which impact the most and/or the least on the perceived benefit, the perceived risk and the device abandonment.

3.6 Study Procedure

The process of writing this thesis was unofficially kicked off in September 2018 when author contacted thesis supervisor to discuss about potential thesis topics. After two months of evaluating several topics, overall scope of the thesis was agreed with the thesis supervisor in November 2018. From mid-November to mid-December around one hundred articles related to the wearable technologies, technology adoption and human behavior were reviewed. This review enabled the author to narrow down the focus of the research and define research questions.

From mid-December until the middle of January, the theoretical chapter of the thesis was written and refined according to the thesis supervisor comments. The rest of the January was spent on writing the research design and methods chapter. During this time, sources for collecting the empirical data was selected and the empirical data was gathered. From the beginning of February until mid-February empirical data of the thesis was analyzed, and key findings were summarized in the findings chapter of the thesis.

Afterwards, the discussion and conclusions chapter of the thesis was written to highlight the main theoretical and practical contributions and to provide suggestions for future research. The final draft of the thesis was sent to the thesis supervisor at the end of February. On the 5th of March, the author and thesis supervisor held a meeting in which the author presented the thesis process and the findings. The thesis manuscript was finalized in the second week of March and then the final version of the thesis was submitted.

4. Findings

4.1 Overview

Across all three products, 307 consumer statements (phrases, sentences or paragraphs) were coded from which 155 were negative and 152 were positive. Garmin Vivosmart HR+ had the most amount of coded statements followed by Polar A370 and Fitbit Charge 2. Overall, there were almost the same number of positive and negative statements across all three products. For Fitbit Charge 2 and Garmin Vivosmart HR+, the number of positive statements were slightly higher than the negative ones. While for Polar A370 the number of negative statements were higher than the positive ones. Table 4 demonstrates a summary of negative and positive consumer statements across all three products.

Table 4. Summary of the number of negative and positive consumer statements across all three products.

	Negative	Positive	Totals
Fitbit Charge 2	42	44	86
Garmin Vivosmart HR+	58	66	124
Polar A370	55	42	97
Totals	155	152	307

In the second round of the analysis, the positive statements were analyzed further based on the perceived benefits factors. While for the negative statements, first it was identified if they belong to the perceived risks or the abandonment. The decision about labeling a statement as the perceived risk or the abandonment was made based on the context of the statement. If the statement was referring to the product pre-purchase considerations, the statement belongs to the perceived risks. While, if the statement was related to the use experience, then it belongs to the abandonment. Majority of the statements found in Amazon reviews were from people who has already used the product. As a result, majority of the negative statements were related to the abandonment. Table 5 demonstrates the number of statements related to the abandonment, the perceived benefits and the perceived risks.

Table 5. Number of statements related to abandonment, perceived benefits and perceived risks across all three products

	Abandonment	Perceived Benefits	Perceived Risks	Totals
Fitbit Charge 2	34	44	8	86
Garmin Vivosmart HR+	54	66	4	124
Polar A370	54	42	1	97
Totals	142	152	13	307

This section provided a brief overview of the findings. In the following sections, findings will be discussed in more detail and will be linked to the two research questions designed in the previous chapter.

4.2 What are the Factors Behind Consumer Decision to Acquire and Use a Wearable Device?

In the theoretical chapter of this thesis, it was discussed that consumers intention to buy and use of a wearable device depends on the perceived value. In other words, if the perceived benefits of a device overpass the perceived risks then the consumer makes the decision to acquire and use the device. Five factors were identified which influence on the perceived benefits: usefulness, ease of use, enjoyment, facilitating conditions and social. Also, five factors were suggested which impact on perceived risks. These factors are: performance, financial, physical, environment and privacy. These factors were used to guide the process of analyzing the collected data.

4.2.1 Perceived Benefits

In total, 152 statements were coded for perceived benefits. 116 of the statements were related to the usefulness, showing the importance of this factor across all the products. There was almost the same number of statements for the enjoyment and the ease of use. There was more emphasis on the enjoyment for Garmin Vivosmart HR+, while there was more emphasis on the ease of use for Polar A370. There were only few statements related to the facilitating conditions and the social factors. Table 6 shows summary of number of statements for the factors influencing perceived benefits.

Table 6. Number of statements for the factors influencing perceived benefits.

	Ease of Use	Enjoyment	Facilitating Conditions	Social	Usefulness	Totals
Fitbit Charge 2	4	4	2	2	32	44
Garmin Vivosmart HR+	3	8		2	53	66
Polar A370	6	2	3		31	42
Totals	13	14	5	4	116	152

Usefulness: findings of this study showed that usefulness is the most influential factor on perceived benefits. In 60 percent of consumer reviews, there was at least one statement about the usefulness. When evaluating the usefulness, several consumers listed out the core functionalities that the device is offering.

“Steps, calories, heart rate, sleep, activities, and health stats. All work pretty good.”

It is important for consumers that the main functionalities are working well, not only in the daily activities, but also when they perform different types of exercises.

“It really keeps a good track of your HR and the numerous exercise regimes suit my day to day lifestyle”

“As a runner, I wanted something with GPS tracking, but not from my phone, and I really wanted the music control. So I'm really overall very happy with the monitor, in terms of what it can do.”

Another factor which impacted on the usefulness of the product is how it can positively influence on the consumer's behavior and making them to adopt positive habits.

“The app is great - motivates you to move periodically but without being intrusive, and provides a lot of data - ranging from simple stuff to quite in-depth data if you want that.”

“Having a relatively sedentary day job it warns you to get up and move”

“One of my personal favorite capabilities of the watch is that it buzzes you every hour that you haven't been actively moving. Just taking a short walk will clear the bar and it makes sure that I don't sit on my bum for the entire day at work (especially since my work has me sitting for majority of the time).”

Beside keeping track of activities during the day, consumers also like to have a device which can help them understand their sleeping habits and help them improve.

“The sleep tracker works well and will definitely indicate if you have an issue with sleep or not.”

“The sleep quality feature is great! It makes me more conscientious of my sleep habits. I love that I get to rate my sleep and see the quality of it on a graph in the Polar Flow app”

From the point of view of the customers, the usefulness of the device is measured in combination with the application/website which analyzes the data and provides feedback to the customer.

“The Garmin Connect site is a data goldmine. I can delve into my mile splits and know exact pacing, cadence, elevation and fastest/slowest paces! I get a detailed map of my route with mile markers on it”

Finally, the usefulness of the wearable devices is not only seen from the core functionalities. But sometimes additional features can be seen very important and differentiates a product from others in the eyes of the consumers.

“I wear gloves at work all day and being able to glance at my watch to see who's calling/texting/emailing me instead of having to take my gloves off every time my

phone buzzes in my pocket is the number one reason I bought this fitness smartwatch."

"I opted for Vivosmart because of the heartrate (HR) capability as well as being able to use my watch as a notification tool. It was a hassle having to bring out my phone all the time and I can manually log in activities (pressing the start/stop button for runs, which is my main workout) without having to rely on Garmin automatically picking up activities."

So, the usefulness of a wearable device is a broad term from the point of view of consumers. They consider a device useful if the core functionalities work well, it suits their exercise routines, it helps them to establish healthy habits, monitor their sleep well and finally facilitate information flow.

Enjoyment: the second most frequent statements were related to the enjoyment, reflecting on how much they enjoy using the wearable devices. In 20 percent of consumer reviews, there was a statement related to the enjoyment. Different features and functionalities were led to the feeling of enjoyment among consumers which may be an indicator that feeling of enjoyment is relative to ones' personality and expectations.

"I ordered the small white band and I love the feel of it. Very comfortable. It's still small enough that it doesn't look bulky on my small wrist."

"I'm also thrilled at being able to swipe the screen a few times to turn my music on without stopping to fiddle with my phone."

"I'm really enjoying it, tracking my workouts is strangely satisfying and I love the reminders about hourly steps."

Ease of use: the third most frequent statements were related to the ease of use. Ease of use is a factor which is closely related to the usefulness as it was discussed in the theoretical background. Most of the statements were focusing on easiness of using the application/interface and the fact that consumers can easily check notifications on the device without the need to check their phone.

"It's super easy to learn/use, especially if you've used Polar devices before. But even if you haven't, it's a breeze to use."

"Using the watch is great. The color display works well and the menus are easy to navigate. In some ways, almost too easy."

"Phone texts appear on screen at the flick of a wrist."

Facilitating conditions: there were only 5 statements about the facilitating conditions. The reason might be that most of the consumers already used and/or interacted with

facilitating conditions such as product brochures and customer support before purchasing the product to get information and find answers to their questions. However, there were still few cases that consumers had perceived the facilitating conditions in particular the customer support beneficial in helping them.

“I reached out to Polar and they had me do a factory reset through Polar Flow, after doing that and resyncing my personal data (took roughly 1 hour because I had some issues resyncing and had to contact Polar again) I was back in business. But after a few weeks it happened again, then suddenly shut off while I was wearing it and would not turn back on. I reached out to Polar. After plugging it in with a couple different USB chargers in various ports on my computer, it finally reset itself. Then after resyncing my personal data, I am, once again, back in business. Hats off to Polar for their excellent and responsive customer service.”

Social: finally, there were only 4 statements about the social factors such as sense of belongingness to a community, ability to share your progress with friends and improved social image.

“The Garmin app also let's you join groups so that you can be better matched for people of your same fitness level. I have Chronic Fatigue Syndrome and was happy to find plenty of CFS groups to join.”

Overall, based on the findings discussed, usefulness is the main factor influencing on perceived benefits. While other four factors seem to have less influential impact on the perceived benefits.

4.2.2 Perceived Risks

In total, 13 statements were coded for the perceived risks. 10 of these statements were related to the performance and the other 3 to the financial risks. There was not any statement found for other three risk factors namely environmental, physical and privacy. One potential explanation might be that these three risks were already considered before purchasing the product, so they are not mentioned in any of the reviews. Another explanation could be that these are not critical factors to consider for fitness trackers. Table 7 shows summary of number of statements for the factors influencing perceived risks.

Table 7. Number of statements for the factors influencing perceived risks.

	Enviornmental	Financial	Performance	Physical	Privacy	Totals
Fitbit Charge 2		1	7			8
Garmin Vivosmart HR+		1	3			4
Polar A370		1				1
Totals		3	10			13

Performance: performance is related to the risks that consumers are aware of and evaluating when adopting and using a wearable device. The majority of consumers' statements were related to a specific functionality or limitation of wearable device which they were aware of before making the purchase, but they still considered it as a risk. Even though, the risk was not high enough at the point of purchase to convince customers to give up on their purchase decision.

“The screen, I hear, is fragile and scratches. I didn't bother taking the risk and get a screen protector.”

“The wrist heart rate monitor is not as accurate as the chest strap, normal for all models like this apparently.”

“The heart rate is out by about ~5%, but that is always going to be the case with this type of HR monitor.”

Financial: there were only three statements related to financial risks, so it is hard to evaluate how important financial risks are from consumers perspective. But based on these statements, cost effectiveness of the product and the potential maintenance cost in the future are considered risky factors in the mind of consumers.

“Strap is not interchangeable, but there are third party sellers that sell replacement straps if you're willing to gamble.”

“It's kind of pricey for what it is - a glitzed up basic fitness tracker with a few more bells and whistles. However, I think you are paying for no chest strap, which is fairly newer technology, and a color, easy to use touch screen.”

Overall, the data collected from consumer reviews provided limited insight for perceived risks. Nevertheless, performance and financial risks seem to have stronger impact, while other three factors have less or no impact at all.

4.3 Why Retention Rate of Wearable Devices is Low?

In the theoretical chapter of this thesis, it was discussed that the abandonment of wearable devices is influenced by eight factors. These factors are: Poor UI and UX design, data inaccuracy, aesthetic design, social pressure, needs and capabilities mismatch, data privacy, other personal factors and other functionality factors. These factors were used to guide the process of analyzing the collected data.

In total, 142 statements were coded for the abandonment from which around 48 percent (68 out of 142) were related to the other functionality factors and 20 percent (29 out of 142) related to the data inaccuracy. During the analysis, it was noticed that there are 13 consumer statements which showed moderate or high level of dissatisfaction from

company customer service, but there was not any suitable code for these statements. As a result, a new code was created called “customer service” and it was added to the list of codes. Table 8 shows summary of number of statements for the factors influencing device abandonment.

Table 8. Number of statements for the factors influencing device abandonment

	Aesthetics Design	Customer Service	Data Inaccuracy	Data Privacy	Needs and Capabilities Mismatch	Other Functionality Factors	Other Personal Factors	Poor UI & UX Design	Totals
Fitbit Charge 2	1	6	4			17	1	5	34
Garmin Vivosmart HR+	2	1	18		2	25		6	54
Polar A370	5	6	7	1		26	1	8	54
Totals	8	13	29	1	2	68	2	19	142

Other functionality factors: surprisingly, most of the consumers’ negative statements were related to the other functionality factors. To give more clarity about the factors causing dissatisfaction, it was decided to investigate further to see if the other functionality factors could be broken down to smaller categories. By reviewing the statements again, it was noticed that many of the consumers are complaining about four main aspects of the products namely: battery life, build quality, synchronization and system malfunction. The remaining three statements were grouped as others. Table 9 demonstrates number of statements for each sub category of other functionality factors.

Table 9. Number of statements for each sub category of other functionality factors.

	Battery Life	Build Quality	Others	Synchronization	System Malfunction	Totals
Fitbit Charge 2	2	11		3	1	17
Garmin Vivosmart HR+	3	6	3	8	5	25
Polar A370	4	5		8	9	26
Totals	9	22	3	19	15	68

As it can be seen from the above table, there were 22 statements from consumers who were dissatisfied with the build quality of the products. The main concerns were about durability of strap and screen, unresponsiveness of touchscreen and problems with charging port.

“After about 5 months, the softness of the band caused the notches that the clasp connects to tear through. The band is way too soft for hard use. Downgrading review to 3 stars as I now have to buy a replacement band way too early for my taste.”

“Touchscreen - it is really bad, after all this time of owning it and having it on constantly (except when going near water) I still haven't been able to successfully cycle through the options without it not registering a touch.”

“One person I know has just had a replacement Charge 2 due to the screen cracking, and her replacement has also cracked!”

“Charger is a little fussy to snap in at times - just make sure you get the battery charging progress bar once you connect.”

Synchronization was mentioned in 19 statements, causing consumers a lot of frustration due to constant need for reconnecting the device to their phone or laptop.

“If you don't sync literally every morning and periodically re-pair with your phone, data will not automatically transfer from device to phone, and it won't allow music control or text alerts. So I feel like the device syncing is clunky and glitchy. It's not a deal breaker for me, since I sync regularly anyway, but I think it could be improved.”

Despite the frustration caused, most of the consumers did not see it as a reason to abandon the device. However, one consumer made the decision to return the device due to synchronization problems.

“I couldn't get the thing to connect with my Galaxy 9+. If I could, it would disconnect and would reconnect. I have a lot of Bluetooth devices and don't have any problems. This did. I ended up returning it.”

Consumers were also complaining about the device malfunction. Several types of malfunction were seen in the statements from which sudden data loss during exercise mentioned the most by the users.

“I purchased this on July 17th and used it for about a month with no issues. After that I noticed that when in workout mode and paired with my H10 HRM, I would get an error saying "something went wrong, please reset the device" and lose all my training data for the workout in progress. Talk about frustrating.”

“The polar A370 keeps crashing about 1 out of 4 workouts, it is extremely annoying to lose all your information after 2hrs exercising! I've done a factory reset twice, keep searching for updates and it keeps crashing.”

Poor battery life was mentioned 9 times. Consumers expressing dissatisfaction for limited battery capacity, forcing them to charge the device sooner than they expect.

“The only thing I question is the battery life, I keep all notifications off all the time but it looks like I am half way through my battery already and its suppose to last several days, so this is questionable.”

Data inaccuracy: In 29 statements, the data inaccuracy caused moderate or high dissatisfaction among consumers. In 3 of the reviews, it was mentioned that the consumer abandoned the device due to data inaccuracy, while the rest only expressed their dissatisfaction.

“I ordered this as a gift for my husband as he preferred some of the options/style of the Garmin compared to the FitBit, (which other members of our family wears). After six weeks of wearing, he continually noticed that not all steps are counted--he noted after continuous use/wear that steps were only counted when there was continuous movement, (as opposed to small steps here-and-there [within his office or around the home, steps were very rarely recognized]). We now have the Garmin sitting idle in our house and have passed the return window--we do not even want to give it away.”

Poor UI & UX Design: the third most frequent factors which caused dissatisfaction among the consumers was poor UI & UX design. Statements focused on many aspects from which difficulty to use the application and low customizability options were mentioned the most.

“While I love the alarm clock, its hard to remember how the heck to find the settings and you have do it through the app (you can't set the alarm or turn it on and off through the device itself, except when the alarm goes off you can snooze it or stop it through the wristband).”

“when I turn notifications on, it sends EVERYTHING to the watch (Samsung Galaxy S7 Edge). It seems if I turn Android system notifications off, it also turns off the messages. When I mean everything, I mean it - when an app updates, when I connect to WiFi, what the weather is, etc. If I use Polar Flow to "block" apps, then I basically get nothing. So, for me, it's a useless feature.”

Customer service: even though customer service is not considered as a part of the product itself, there were 13 statements related to dissatisfaction about customer service. In one statement, it was emphasized that since customer service did not change faulty device, the product was abandoned and returned to the reseller.

“So I decided to return it. Polar does not seem to care that the device keeps restarting, they claim its only mine when I have told them repeatedly it occurs to others as well such as my friends. Too bad because the HR sensor was fantastic.”

“Still awaiting replacement strap! 8 weeks later, keep asking me to wait another 2-3 weeks. Disgraceful. Won't provide a new Fitbit overall, going to contact trading standards.”

Aesthetics design: there were 8 statements related to aesthetics design. Consumers were displeased with how the product looks like or it did not feel very comfortable for all day wear. However, aesthetic design did not seem like to be a reason to abandon the device.

“I'm so displeased with how ugly and long this new one is that I'm switching back to my A360 band (thankfully old band is compatible with A370). I don't know why

they would make the new one longer when there are already medium-large sizes available...”

Needs and capabilities mismatch: there was only two statements related to this factor which caused very minor dissatisfaction for the consumers.

“Only wish the "Other" workout setting was customizable; I would like to have a weight lifting setting.”

Other personal factors: there were two statements related to this factor. One person was dissatisfied with limited color choices and the other one experienced skin reaction from strap holder.

“I get a skin reaction where the loop for the strap holder touches my skin. It irritates and blisters and I have to change wrists while my left heals.”

Data privacy: only one statement found related to the data privacy, being displeased of sharing data with the company, while the benefit is only one sided.

“You also have to agree to let them sell your data to companies. I’m not winning at all in this situation because I’m not getting compensated and I’m the one who is giving your company feedback by using your watch.”

Overall, analysis done on the consumer data revealed that other functionality factors (battery life, build quality, synchronization and system malfunction), data inaccuracy and poor UI & UX design are the most frequent factors behind customer dissatisfaction. While influence of other factors seem to be less significant. In few cases, consumers explicitly mentioned that they are abandoning/returning the device. However, in most cases, they were only expressing feeling of dissatisfaction and it cannot be clearly concluded if it will result to the abandonment of the device or not.

5. Discussion and Conclusions

5.1 Study Overview

Reduction in the daily level of physical activities and the development of chronic health conditions due to the inactivity have become a growing concern (Wilde et al., 2018). Several reasons are associated to the inactivity, such as the lack of motivation and limited knowledge on how to include physical activities in the daily life (Ananthanarayan & Siek, 2012; Rupp et al., 2016). To address the inactivity among individuals, many health and life style technologies have been introduced in the past years (Kerner & Goodyear, 2017) and research on these technologies has become more and more popular among scholars.

This thesis aimed to contribute to the endeavor of understanding factors influencing consumers' adoption and use of wearable technologies. For this purpose, literature on human behavior, human motivation, theories and models of technology adoption, and previous empirical studies on the adoption and effectiveness of wearable technologies were reviewed. Literature review resulted the identification of factors influencing the adoption and abandonment of wearable technologies, which were illustrated in the theoretical framework of this thesis (Figure 15). In order to validate the theoretical framework, an empirical study was conducted using netnography method. Data required for the study was gathered from top rated consumer reviews of three selected products, and then analyzed using Atlas.ti. Factors presented in the theoretical framework of the thesis were utilized to guide the process of analyzing the collected data. Finally, findings of the study were shown in detail by quantifying frequency of statements about different factors and providing direct quotations from consumer reviews.

The remaining of this chapter aims to discuss theoretical contributions of this thesis by highlighting key findings and comparing them with findings of other relevant empirical studies. Then, practical contributions of the thesis are discussed, giving suggestions and recommendations for brands and wearable manufacturers on how to improve the functionality and design of their products. Finally, limitations of the study are explained and some suggestions for future research are given.

5.2 Theoretical Contributions

This thesis provides several theoretical contributions and adds to the limited research done on factors influencing the adoption and use of wearable technologies. These contributions are explained in detail in the following paragraphs.

Perceived benefits: findings of this thesis support prior research that usefulness has a significant impact on the adoption and use of wearable technologies (Davis et al., 1989;

Kim & Shin, 2015; Lunney et al., 2016). Enjoyment is found to be influential on the consumer's perceived value, but its impact is expected to be less than usefulness. Results of studies done by Gu et al. (2016), Yang et al. (2016) and Gao et al. (2015) also show that enjoyment (also referred to as hedonic motivation) has strong influence on perceived benefits. In addition, the enjoyment has a bigger influence on actual users in the comparison with potential users (Yang et al., 2016). Potential users tend to pay more attention to the usefulness of the wearable device, while actual users put extra value on the pleasure gained from using the device. Similar to the enjoyment, the ease of use influences on the perceived value. The ease of use is closely related to the usefulness, and in some cases, it is hard to separate these two factors from each other, which is also found in prior research (Davis et al., 1989, Kim & Shin, 2015; Lunney et al., 2016; Gu et al., 2016).

Facilitating conditions do not have significant impacts on the perceived value. This is aligned with study done by Gu et al. (2016). They also argued that facilitating conditions are important in creating initial trust, but do not have significant impacts on the adoption of wearables. Finally, findings of this study show that social factors do not have significant impacts on consumers' perceived benefits. However, Yang et al. (2016) found that both potential and actual users tend to consider how using a wearable device can improve their social image. The difference between the findings could be related to the study methods. In their study, Yang et al. (2016) designed survey questions for measuring perceived value of wearables' social image. But in this thesis, statements of consumers were collected from product reviews, and there was not any influence on the content. So, even though people may not discuss the impact of social image on their decision to use a wearable device, it might have a strong impact on their decision.

Perceived risks: findings of this thesis provide rather limited insight about the consumer's perceived risks of wearables. The main reason is that all consumer reviews gathered for this study were from people who have already used a wearable device for a certain period of time. So, their statements were mainly related to dissatisfaction and potentially the abandonment rather than perceived risks. However, in some consumer reviews, consumers were referring to their risk considerations during the wearable adoption. Based on consumers' statements, performance has the most impact on perceived risks. Yang et al. (2016) had a similar finding in their study. They argued that for potential users, the performance risk is very critical, and potential users need to have some assurance that the device will not malfunction in the future.

Financial risks are also seen to be influential on the perceived risks, although the impact is less significant. Both Yang et al. (2016) and Kim & Shin (2015) had similar findings in their studies. There was no evidence found in this study to support that privacy, physical and environmental factors have any influence on consumers' perceived risks. However, in prior research, there are some evidence supporting their impact on consumers adoption. Regarding privacy risks, Gao et al. (2015) found that among both

fitness device users and medical device users, privacy risks are important considerations. Physical risks are also found to be important due to the potential impact of wearable devices on human health (Kalantari, 2017). Finally, in a study done by Hwang (2016), environmental factors were found influential on consumers' adoption to the solar-powered clothing. One potential reason for not finding any statements to support consumers' consideration of privacy, physical and environmental risks is that these factors are mainly evaluated before purchasing a product. So, it is less likely to find consumer statements regarding these risks on Amazon product reviews. Another explanation could be that these risks are perceived more for other types of wearable devices such as textile clothing and smart glasses, not for a product such as an activity tracker which is a more established and widely used technology.

Device abandonment: this thesis revealed that data accuracy is the main reason behind consumers' dissatisfaction and abandonment of wearable devices. Since majority of consumers adopt to a wearable device in order to get a better understanding of their body, inaccuracy in the data collection significantly diminishes the value of the device. This finding is aligned with many other empirical studies which also found the significance of the data inaccuracy in device abandonment (Salah et al., 2014; Harrison et al., 2015; Piwek et al., 2016; Epstein et al., 2016; Schrager et al., 2017). The build quality is the second important factor behind consumers' dissatisfaction and abandonment. Consumers get very displeased when they experience issues such as screen cracks, loose connection ports, the low-quality wrist band and so on. Even though the build quality is very important, there is limited discussion about it in prior research. So, this is one area where this thesis adds to the relevant literature.

Poor UI & UX design, synchronization, system malfunction and battery life cause a lot of annoyance and dissatisfaction among consumers with a slightly lower impact in comparison to the data inaccuracy and the build quality. Since wearable devices are intended to be used continuously, users expect to have an easy time to navigate in the device and be able to easily connect it to their phone or other devices for data transfer. Constant synchronization issues and system malfunctions could build up a lot of frustration among consumers, resulting to the abandonment of the device. One factor which was not discussed in the prior research is the importance of the customer service. When a customer faces an issue with his/her device, the quality of the customer service has a big impact. The poor customer service could cause additional frustrations among customers, even leading to abandonment of the device. However, the good customer support could result to the reduction of dissatisfaction and annoyance, decreasing the possibility of the abandonment.

Aesthetic design has some impacts on dissatisfaction and the potential abandonment, but its impact is much less significant. This finding is aligned with studies done by Salah et al. (2014), Schrager et al. (2017) and Harrison et al. (2015) which all concluded that aesthetic design can lead to the device abandonment, but it is less influential in

comparison to factors such as the data inaccuracy. Finally, the data privacy, needs and capabilities mismatch, and other personal factors show very minimal impacts on the device abandonment. The main reason could be that many people are already familiar with the data privacy regulations and they familiarize themselves with capabilities of wearable devices before making a purchase decision.

Research method: this thesis is among the first, to use netnography as a data collection method. Most of the reviewed empirical studies used surveys, interviews or a combination of both to gather empirical data. The only exception was the study done by Clawson et al. (2015) who analyzed advertisements for secondary sales of self-tracking devices on Craigslist. Utilizing netnography enabled this study to look at consumers reasoning behind adoption and abandonment of wearable devices from a new perspective, adding value to the related field of research.

5.3 Practical Contributions

The findings of this thesis provide meaningful and actionable insights for wearable brands. First, the most important reason why consumers buy a wearable device is usefulness. Therefore, it is important to make sure all core functionalities of the wearable device work perfectly. In case of activity trackers, it is critical that sensors pick up activity data consistently and accurately. Otherwise, there is a high chance that customers feel dissatisfied and stop using the device. One suggestion would be not only to test the product in laboratory conditions, but extensively in real life activities for instance by launching it to the restricted audience or specific markets (ex. soft launch).

Second, wearable devices specially activity trackers are meant to be used continuously. Therefore, it is important to build these devices out of durable material resistance to water, hot and cold temperature, and relatively resistance to force and pressure. As it was shown in the findings of this thesis, customers get very disappointed and sometimes even quit using the device if after a few months of use, the wrist band needs to be replaced or the screen is cracked. In addition to the high build quality, it is recommended to have customizable designs. Wearable devices such as fitness trackers are visible in public. So, they are not only considered as fitness items, but they should match with users' outfit in different situations. Providing a wider variety of designs and colors would allow users to purchase a product which is suitable for their lifestyle and outfit.

Third, customers expect an easy-to-use and smooth user interface and functionality from wearable devices. Specially for devices with wider set of functionalities, customizability of user interface is very important. Moreover, wearable devices are meant to be compatible with a large set of devices, especially smart phones. Wearable manufactures should perform extensive tests to make sure their device is compatible with other devices and the synchronization is done fast and effortless.

Finally, it is not only important to have a high-quality product, but the superb customer service as well. Customers want to have some assurance that they are not alone if they faced any problem while using the device. Setting up the active customer support team who is trained about the most common issues, is very important to make customers satisfied and make sure they do not abandon the device due to the annoyance and the frustration. In addition, it would be very helpful if the customer support team keeps in touch with customers regarding new software/product updates, making sure customers are informed about changes and updates.

5.4 Evaluation of the Study

The main objective of this thesis was to gain a better understanding of factors influencing consumers' adoption and use of wearable technologies. For this purpose, around one hundred articles related to wearable technologies, technology adoption and human behavior were reviewed. Based on the findings of the literature review, the theoretical framework of the thesis was built. This theoretical framework provided a good understanding on factors influencing both adoption and use of wearable technologies. It can be argued that reviewing more scientific materials could have led to finding more factors influencing the adoption and use. However, after reviewing several technology adoption theories and models, and empirical studies on wearable devices, it was realized that there is a lot of similarities in the findings. So, the author reached to the conclusion that reviewed articles are adequate as the basis of the theoretical framework.

An empirical study was designed to evaluate the theoretical framework of the thesis. Both quantitative and qualitative methods were considered to gather the empirical data. However, it was decided to select qualitative study mainly due to the limited number of qualitative studies on wearable technologies. From the qualitative methods available, netnography was chosen. The main reason for selecting netnography was that it is far less obtrusive than some other methods such as focus groups and interviews. Of course, it would have been ideal to use several methods to gather qualitative data and compare the findings and effectiveness of each method.

The scope of the thesis was narrowed down to activity trackers, and only three products were selected based on criteria such as functionalities, brand name and price. Limiting the scope of the thesis to one category of wearable technologies, and to only three products might have some influence on comprehensiveness of the findings. Wearable devices have many similar characteristics, and some findings of this study should be applicable to other wearable devices as well. However, there might be factors influencing the adoption and use which are specific to a certain category of wearable devices, and as a result not found in this study.

Amazon was selected as the main source for the data collection because it had almost all the criteria for an ideal online community. Amazon has high traffic of posts, large number

of people participate in discussions, almost all wearable devices are sold on the platform and there are many detailed and rich posts suitable for qualitative research. However, there are some downfalls in selecting Amazon as well. No demographic information is publicly available for Amazon users meaning there is no option to analyze the data from aspects such as the age and gender.

When conducting qualitative study, there is always a question on how many interviews should be conducted or how many customer reviews should be analyzed. The simple answer is as many reviews as needed until no new insight is generated. After reading and analyzing 10 to 15 customer reviews, author noticed the repetition in the comments and the fact that no new insight is being generated. Therefore, 20 reviews seemed to be adequate for each selected product. However, one downside of collecting reviews only from Amazon.com was the limited diversity in geographical location. Almost all the users in Amazon.com are from the United States. So, this study cannot verify if the findings are applicable in other geographical locations due to factors such as influence of culture on consumers' perception.

Finally, the data collected in this thesis was analyzed in Atlas.ti which is a well-known software for analyzing qualitative data. All the customer statements were reviewed by the author which gives consistently to the way data was labeled and categorized. However, this increases the possibility of subjectivity in evaluating customer statements. Moreover, the collected data was quantified by counting number of statements related to a specific factor which in turn showed the importance of that factor in the eyes of customers. Since the data was collected from Amazon, which mainly has reviews from people who already purchased and used the wearable device, there was limited findings for perceived risks. Therefore, drawing a comprehensive conclusion based on the limited data on perceived risk factors was challenging and the findings might not be applicable to other wearable devices.

5.5 Future Research

There has been a growing interest in studying wearable devices in the past years. This study aimed to play a small role to gain a better understanding of factors influencing consumers' adoption and use of wearables. One suggestion for future research would be conducting larger scale netnography, by collecting data from various geographical locations with wider product selection and larger number of reviews. This will help in gaining a better understanding on potential impacts of geographical location and wearable device models on consumers perceptions.

Another suggestion for research is looking deeper to see if there is any relationship between individuals' personality and effectiveness of wearable devices in encouraging healthy behavior. Many people adopt to wearable devices hoping to become motivated in performing physical activities in their daily life. As this study shows, there are several

product related factors which lead to the abandonment of wearable devices. However, it would be interesting to see how much personality traits impact on an individual's perception of effectiveness of wearables.

Moreover, as it was found in this study consumers are hoping for the durability, comfort and visual attractiveness, at least when it comes to fitness trackers. This could open many interesting opportunities related to the design of wearable devices. For example, finding the answer to questions such as what new materials could be used in building wearable devices which are sustainable, visually pleasing and durable, could be very valuable for both wearable manufacturers and end users.

Finally, adding a wider range of functionalities to wearable devices means an increase in the energy consumption. This study found that consumers are hoping for less downtime of wearable devices due to charging the battery. One potential area for future research could be related to optimizing energy consumption of the devices and at the same time improving battery efficiency. Developing new battery technologies which could enable the device usage for a longer period could be very valuable for both manufacturers and consumers.

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Appendix A

How product reviews were collected from Amazon:

First, navigate to brand official product page in Amazon, select customer reviews and then press all customer reviews

Polar A370 Fitness Tracker with 24/7 Wrist Based HR

by Polar



256 customer reviews | 241 answered questions

Amazon's Choice

for "Polar a370"

Then, sort customer reviews by top rated

SORT BY

FILTER BY

Top rated ▼

All reviewers ▼

All stars ▼

Text, image, video ▼

Showing 1-10 of 256 reviews

Appendix B

An example of one top rated customer review for Polar A370 can be seen below:



WallyD

★★★★☆ **Battery Life Is Unacceptable**

February 26, 2018

Color: Black | Size: Medium/Large | **Verified Purchase**

Updated Review: I have returned the A370 to Amazon.

When my wife and I had 3 Fitbits go bad in the space of not much more than a year, I decided it was time to try another brand. I already had a Polar H7 heart rate monitor (HRM) with chest strap and was really pleased with it (I give it 5 stars) and the Polar Beat app (4 stars from me) which I used during workouts. I have a lot of Garmin products and really like them, but they're for navigation, not fitness. Two things struck me as I looked at the Garmin Vivoactive and somewhat similar Polar A370 customer satisfaction scores on Amazon: First, both had a lot of reviewers giving poor marks (1 or 2 stars); the Polar had 29% of reviewers give poor marks while Garmin had 23%, and second there were only 106 reviews for Polar compared to 2964 for Garmin (and more than 10,000 for the Fitbit which I will never use again). Apparently not many people buying Polar.

I decided to look at both the Garmin Vivoactive and Polar A370 before buying. The Garmin was everywhere but I couldn't find Polar. As a result I contacted Polar Customer Service and asked what stores in the greater Seattle area carried their products; amazingly, they couldn't tell me. Ultimately I decided to buy the Polar A370 for continuity and compatibility with my database on Polar's web site as well as my satisfaction with the Polar Beat App and my Polar H7 HRM.

After a week and a half I have decided to give the Polar A370 3 stars and not recommend it for people not already Polar customers familiar with Polar. After 3 weeks I decided to return the product and downgraded my rating to 2 stars

- Similar to the observations of multiple people who gave the A370 only 1 or 2 stars, I find that the BATTERY IS UNACCEPTABLE. I have to charge the battery twice a day in order to wear the A370 day and night. The battery only lasts 10 to 15 hours 1 star for the battery.
- Pairing the A370 is usually a frustrating task. I have half a dozen items that I pair with my phone using Bluetooth; only the A370 gives me trouble. It normally takes me 4 or 5 tries to get a pair. Frequently I get a message on both the A370 and my phone that the devices are syncing then I get a message on the A370 that says the sync failed. I also frequently have to enter a 6 digit number on my phone to authorize the A370 – this is the only device I have which requires this. 1 1/2 stars for Bluetooth.
- In order to use the A370 you have to have the Polar Flow app on your phone (not Polar Beat which is specifically for capturing heart rate and monitoring exercise). The app is not at all intuitive and there are no instructions (per contact with Polar Customer Service). I do like seeing what my heart rate was during the night. 3 stars for the Polar Flow app
- Progress against my activity goal is measured constantly and reported to me as a percentage. Problem is I have no clue what my activity goal is. The only goal I can set is a nebulous statement about how active a person I will be – no way that I have found to set metrics. My (failed) Fitbits were much better at goal setting and monitoring progress. 2 stars for goal setting.

48 people found this helpful

Helpful

▼ Comment | Report abuse